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Persistence of Childhood Obesity

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Abstract

Rates of childhood obesity have increased dramatically in the last decades but little is known about the origins of, or persistence in, childhood obesity. In this paper, we attempt to answer three questions. First, how does weight status evolve from birth through primary school? Second, what is the causal effect of past weight status on the future weight status of children? Third, how important are time-varying and time-invariant factors in the dynamics of childhood obesity? We find that weight status is highly persistent from infancy through primary school and most of this persistence is driven by time-invariant factors that are determined prior to birth. Future research is needed to identify these factors.

Keywords: Childhood obesity, persistence, fetal origins hypothesis

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1 Introduction

The prevalence of obese adolescents in the United States has tripled in the last thirty years; it has more than doubled for younger children. Defined as having an age- and sex-adjusted body mass index (BMI) above the 95th percentile (of the reference distribution), the prevalence of obese children increased from 5% to 12.4% for 2-5 year old children and from 5% to 17.6% for 12 to 19 year-olds between 1976 and 2006 (Ogden et al. 2008). In addition, vast differences in the time trends of BMI increases have been documented: the incidence of obesity among white girls aged 12-19 has increased from 7.4% to 14.5% between 1988 and 2006, whereas the corresponding figures for African-American girls are 13.2% and 27.7% (Ogden et al. 2002; Ogden et al. 2008). Deckelbaum and Williams (2001, p. 242S) conclude that “childhood obesity is increasing at epidemic rates, even among pre-school children...” More recently, Brisbois et al. (2012, p. 347) state: “Obesity is considered to be a worldwide epidemic with little evidence that its incidence is declining or that it has even reached a plateau.”²

As childhood obesity has received greater attention, its consequences have become increasingly well-documented. Obesity burdens individuals with physical, economic, and emotional suffering, and puts children and adolescents at risk for a number of health problems such as those affecting cardiovascular health, the endocrine system, and mental health (Deckelbaum and Williams 2001; Krebs and Jacobson 2003). Dietz and Gortmaker (2001) note that 60% of overweight children aged five to ten years old have at least one associated cardiovascular disease risk factor. Finkelstein and Zuckerman (2007) report that if the childhood obesity epidemic continues unabated at the current rate, as many as 30-40% of the US population will develop Type 2 Diabetes during their lifetime. A memorandum signed by President Obama on February 9, 2010 states³:

“Across our country, childhood obesity has reached epidemic rates and, as a result, our children may live shorter lives than their parents... One third of all individuals born in the year 2000 or later will eventually suffer from diabetes over the course of their lifetime, while too many others will face chronic obesity-related health problems such as heart disease, high blood pressure, cancer, and asthma. Without effective intervention, many more children will endure serious illnesses that will put a strain on our health-care system. We must act now to improve the health of our Nation’s children and avoid spending billions of dollars treating preventable disease.”

In the US, the total cost attributable to obesity was over \$75 billion in 2000 according to Finkelstein et al. (2004). More recent estimates put the cost over \$200 billion (Cawley and Meyerhoefer 2012). Walpole et al. (2012) calculate that North America accounts for 34% of the total human biomass in the world despite containing only 6% of the world population. Moreover, the authors estimate that if the entire world had the same BMI distribution as the United States, this would be equivalent to an additional 935 million people in the world of average BMI.

While the changes in childhood obesity rates across cohorts, as well as the consequences of these increases, are well-documented, much less is known about how child weight evolves over the life cycle for a given individual. How

²There is some evidence of rates plateauing in the United States. For the most recent figures, see <http://www.cdc.gov/obesity/data/childhood.html>.

³See <http://www.whitehouse.gov/the-press-office/>.

persistent is childhood obesity? Does this persistence vary by age, race, gender, or location? What are the origins of any persistence? Specifically, what is the relative importance of state dependence (i.e., a causal effect of past weight status on future weight status), unobserved heterogeneity (i.e., unobserved genetic or environmental risk factors), and observed heterogeneity (i.e., commonly measured risk factors)? These are fundamentally important questions for researchers as well as policymakers. If weight is persistent, then early intervention is preferable to waiting until adolescence or beyond. However, if persistence varies by age, then the optimal timing of policy interventions may be further refined such that child weight is reduced prior to the degree of persistence becoming elevated.⁴ Finally, and perhaps most importantly, if persistence is due to persistent underlying factors rather than state dependence, then only by altering these factors can children be moved to a different trajectory. Unfortunately, the existent literature has not delved sufficiently deep into the sources of any persistence.

To examine these fundamental questions, we apply nonparametric and parametric methods commonly employed to analyze income mobility. Individual income mobility refers to the ability of an individual to move up or down in the income distribution throughout one’s lifetime. Intergenerational income mobility refers to the ability of an individual to move up or down in the income distribution of one’s own generation relative to where one’s parents were in their generation’s income distribution. Documenting patterns in individual or intergenerational income mobility has a lengthy history. As such, empirical methods designed to assess movements over time in the distribution of income are well developed. Here, we borrow this knowledge in order to study movements over time in the distribution of anthropometric measures.

We apply these methods to data from the Early Childhood Longitudinal Survey – Kindergarten Cohort (ECLS-K). The ECLS-K is a nationally representative longitudinal survey of children entering kindergarten in Fall 1998. In addition to providing information on birthweight, anthropometric data is collected at several points in time between kindergarten and eighth grade. We then supplement this analysis by examining data from the Early Childhood Longitudinal Survey – Birth Cohort (ECLS-B). The ECLS-B is a nationally representative longitudinal survey of children born in the U.S. in 2001. Information is provided on these children at ages 9 months, two years, four years, and five years. Thus, the ECLS-B sample allows for a more refined examination of weight trajectories prior to kindergarten entry.

Our findings are striking. In particular, we observe four key findings. First, weight, height, and BMI are *highly persistent* starting in *early* infancy. Second, *heterogeneity* is important. Consequently, a singular approach to the obesity epidemic is unlikely to be successful. Important sources of heterogeneity include: demographics, initial conditions, outcome measure, age range, and metric used to measure persistence. Third, children from more *disadvantaged* households show less mobility and greater persistence in weight status. As such, more disadvantaged children are more likely to find themselves on an “obesity trajectory” earlier in life. Finally, the vast majority of persistence is attributable to *time invariant* characteristics of children. This finding is of critical importance as it

⁴For instance, an article in the *New York Times* on March 22, 2010 states that some evidence now suggests that children may become entrenched “on an obesity trajectory” even before kindergarten; however, the evidence is not “ironclad” (<http://www.nytimes.com/2010/03/23/health/23obese.html>). Public health officials tend to advocate school-based reforms in light of the near universal enrollment, yet others stress the importance of preschool interventions (e.g., Frisvold and Giri 2011; Dietz and Gortmaker 2001; Davis and Christoffel 1994). Eriksson et al. (2001, p. 735) conclude that “obesity is initiated early in life.”

implies that the only interventions that will have a substantive, long-run effect on a child’s weight status are those that alter these salient, time invariant attributes. Thus, current policy interventions may, at best, have a marginal impact in the short-run and, at worst, be destined to fail. Moreover, what these critical, time invariant attributes are is difficult to say given the data at hand. We find some evidence that fetal nutrition – as proxied by mother’s pre-pregnancy weight and weight gain during pregnancy, gestation age, birth status (singleton, twin, or higher order birth), and birthweight – impacts the evolution of child weight over the life cycle. However, *unobserved*, time invariant attributes play a much more prominent role.

The notion that attributes determined at or shortly after birth, and thus time invariant over early childhood and adolescence, play a dominant role in the evolution of obesity is consistent with the strong evidence in economics and elsewhere on the so-called fetal origins hypothesis (see, e.g., Almond and Currie 2011). The fetal origins hypothesis, also referred to as the thrifty phenotype hypothesis or Barker’s hypothesis (due to Barker’s original publication in 1992), posits long-run effects of conditions *in utero* during critical periods of development through “programmed” changes in the physiology and metabolism of individuals (Barker 1997). An article in *Time* on September 22, 2010 summarizes⁵:

“[P]ioneers assert that the nine months of gestation constitute the most consequential period of our lives, permanently influencing the wiring of the brain and the functioning of organs such as the heart, liver and pancreas. The conditions we encounter in utero, they claim, shape our susceptibility to disease, our appetite and metabolism, our intelligence and temperament. In the literature on the subject, which has exploded over the past 10 years, you can find references to the fetal origins of cancer, cardiovascular disease, allergies, asthma, hypertension, diabetes, obesity, mental illness — even of conditions associated with old age like arthritis, osteoporosis and cognitive decline.”

Our analysis here is consistent with this view, the implications of which are quite profound. If correct, the most efficient interventions to curb obesity may need to start prior to birth. Deckelbaum & Williams (2001, p. 239S) conclude:

“Novel approaches in the prevention and treatment of childhood overweight and obesity are urgently required. With the strong evidence that a lifecycle perspective is important in obesity development and its consequences, consideration must be focused on prevention of obesity in women of child-bearing age, excessive weight gain during pregnancy, and the role of breast-feeding in reducing later obesity in children and adults. Consideration must be given to family behavior patterns, diet after weaning, and the use of new methods of information dissemination to help reduce the impact of childhood obesity worldwide.”

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the prior literature. Section 3 presents the empirical methodology. Section 4 introduces the data. Section 5 discusses the results and their implications. Section 6 concludes.

⁵See <http://www.time.com/time/magazine/article/0,9171,2021065,00.html>.

2 Related Literature

The persistence of childhood overweight status into adulthood has been documented in a number of studies. Whitaker et al. (1997) found that the probability of an overweight six year-old child becoming an obese adult is 50% compared to 10% for a non-overweight child. In addition, the risk of becoming obese in adulthood is exacerbated by having an obese parent. Eriksson et al. (2001) found that individuals were three times more likely to be obese as an adult if they had a BMI greater than 16, as opposed to below 14.5, at age seven.⁶ Nader et al. (2007) find that children who were overweight prior to age of five are five times as likely to be overweight at 12 relative to children who were not overweight prior to age of five.

Freedman et al. (2001) also report a strong relationship between overweight status in childhood and adult BMI. However, most striking is that obese adults who were overweight prior to age eight have a much higher BMI than individuals suffering from adult onset obesity (41 versus 35). In a later study, Freedman et al. (2005) document significant differences in the transmission of BMI from childhood to adulthood along racial lines. The authors find that not only are overweight black children more likely to become obese adults than similar white children, but also that “relatively thin (BMI \leq 50th percentile) white boys were more likely to become overweight adults than were their black counterparts” (p. 928). Iughetti et al. (2008) provide an excellent summary of the literature on persistence in obesity. They also present evidence that overweight status among children is persistent not only in the US, but also in Italy. Gable et al. (2008) analyze the relationship between socioeconomic status, overweight persistence, and school outcomes. The authors find that family socioeconomic status is predictive of both the probability of a child being overweight and the probability of persistence of overweight status.

Finally, Van Cleave et al. (2010) analyze changes in the prevalence of obesity and other chronic conditions (e.g., asthma, other physical and learning conditions). The authors find that prevalence of obesity is increasing and is highly persistent over time. Conversely, many children with chronic conditions at ages two through eight did not have the condition six years later. Deckelbaum and Williams (2001, p. 239S) conclude: “Disturbingly, obesity in childhood, particularly in adolescence is a key predictor for obesity in adulthood.” Similarly, Dietz and Gortmaker (2001, p. 340) state: “The best evidence suggests that the majority of overweight adolescents go on to be overweight adults.”

More generally, others have investigated persistence in health among adolescents and adults. For example, Halliday (2008) investigates persistence in self-reported health status among white adults age 22-60 using data from the PSID and allows the parameters of the model to be group-specific. The results suggest that the degree of state dependence – the causal effect of past states on one’s current state – in health is modest for half the population, yet it explains much of the observed persistence in health for the other half. Goeree et al. (2011) analyze persistence in bulimia nervosa in young women. The authors find a substantial role for state dependence in the persistence of bulimia nervosa, thus justifying the importance of early intervention.

In light of these relationships and because of the strong effects of being overweight in childhood on the development of chronic health problems, Dietz and Robinson (2005) suggest that “treatment to achieve weight maintenance is

⁶A BMI of 14.5 and 16 lie in the ‘normal’ range; roughly the 60th percentile for a BMI of 16 and the 25th percentile for a BMI of 14.5.

recommended” for two to six year-old overweight children (p. 2102). In January 2010, the US Preventive Services Task Force have issued new guidelines suggesting that doctors regularly screen the weight of children aged six and over and refer children to specialized weight management programs if needed.⁷ However, evidence in support of the fetal origins hypothesis suggests that none of these recommendations may be sufficient. Instead, prenatal and even preconception interventions may be needed.

As stated earlier, beginning with Barker’s work, there is a strong belief that *in utero* events may determine whether a fetus ends up on an “obesity trajectory.” Deckelbaum & Williams (2001, p. 239S) note that “emerging data suggest associations between the influence of maternal and fetal factors during intrauterine growth and growth during the first year of life, on risk of later development of adult obesity and its comorbidities.” More recently, Brisbois et al. (2012, p. 347) state: “Based on recent evidence, early-life experiences *in utero* and postnatal influences may induce permanent changes in physiologic function that programme the long-term regulation of energy balance. This subsequently may adversely impact obesity risk in later life.”

Which factors may induce such permanent changes in order to set a fetus upon an “obesity trajectory” is the subject of on-going research. While initial hypotheses focused on undernutrition and oxygen supply, additional factors such as maternal BMI, maternal weight gain, maternal smoking, gestational diabetes requiring insulin, and postnatal characteristics such as breastfeeding and the timing of introduction to solid foods are also found to be important (Dietz 1997; Deckelbaum and Williams 2001; Brisbois et al. 2012).

In a final strand of literature, researchers are attempting to identify early life predictors of future obesity during childhood and adulthood. Such research has focused on identifying physical indicators of an infant’s predisposition to future obesity. Early conclusions suggest that birthweight, length, and gestation age at birth alone are not strong predictors. Instead, there are complex interactions between these measures, along with other measures such as head circumference, that matter. For example, a fetus born prematurely and, as a result, with low birthweight and length is not likely to be at greater risk of future obesity as long as the fetus’ measurements are in proportion and within ‘normal’ ranges given its gestation age. On the other hand, a fetus born with disproportionate physical measurements suggests a greater risk (Barker 1997; Sayer et al. 1997; Godfrey and Barker 2001; Brisbois et al. 2012).

3 Empirics

To examine the dynamics of early childhood weight status, we draw upon methodologies developed in the labor economics literature. Many studies within labor economics are concerned with the persistence of economic outcomes – such as income – and the sources of such persistence. The first approach utilizes several nonparametric measures of mobility. These measures shed light on movements over time by individuals within a distribution. Moreover, splitting the sample into distinct groups on the basis of age or other economic or demographic characteristics provides evidence of differences in persistence across these groups. The second approach utilizes dynamic regression models to assess persistence. This approach can also be used to examine possible mechanisms underlying persistence.

⁷See <http://www.ahrq.gov/clinic/uspstf/uspsschobes.htm>.

3.1 Nonparametric Approach to Persistence Measurement

To begin, we assess the degree of overall persistence in child weight using several metrics commonly used to measure income mobility. Applying these metrics to different subgroups of the data, we are also able to analyze differences in persistence across socio-demographic groups, as well as across early stages of the life cycle.

To proceed, define the following notation. Let y_i^t , denote the weight outcome of child i , $i = 1, \dots, N$, in period t , $t = 1, \dots, T$. Further, let $F_{t_0, t_1}(y^{t_0}, y^{t_1})$ denote the joint (bivariate) cumulative distribution function (CDF) of child weight in two distinct periods, t_0 and t_1 , where $t_0 < t_1$ and $y^t \equiv [y_1^t \cdots y_N^t]$.

While movement through the distribution from an initial period, t_0 , to a subsequent period, t_1 , is completely captured by $F_{t_0, t_1}(y^{t_0}, y^{t_1})$, this is not practical. One method by which to summarize this joint distribution is via a $K \times K$ transition matrix, P_{t_0, t_1} , with representative element

$$p_{kl}^{t_0, t_1} = \frac{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0}, \zeta_{l-1}^{t_1} \leq y^{t_1} < \zeta_l^{t_1})}{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0})} \quad k, l = 1, \dots, K \quad (1)$$

where $0 < \zeta_1^s < \zeta_2^s < \cdots < \zeta_{K-1}^s < \infty$, $\zeta_0^s = 0$, and $\zeta_K^s = \infty$, $s = t_0, t_1$, are cutoff points between the K weight classes.⁸ Thus, $p_{kl}^{t_0, t_1}$ gives the fraction of children in weight class k in period t_0 who are in weight class l in period t_1 . Note, inclusion of the denominator in (1) standardizes elements of the transition matrix such that each row and column sums to unity. A complete lack of mobility implies $p_{kl}^{t_0, t_1}$ equals unity if $k = l$ and zero otherwise. Finally, we can define *conditional* transition matrices computed using sub-samples with $X = x$, where X denotes a vector of individual attributes. Denote the conditional transition matrix as $P_{t_0, t_1}(x)$, with representative element

$$p_{kl}^{t_0, t_1}(x) = \frac{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0}, \zeta_{l-1}^{t_1} \leq y^{t_1} < \zeta_l^{t_1} | X = x)}{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0} | X = x)} \quad k, l = 1, \dots, K. \quad (2)$$

Implicit in this definition is the assumption that X are time invariant attributes.

Recently, Bhattacharya and Mazumder (2011) present an alternative characterization of the joint distribution $F_{t_0, t_1}(y^{t_0}, y^{t_1})$ to better assess *upward* and *downward* mobility. Their measure of upward mobility is defined as

$$v_{kl}^{t_0, t_1} = \frac{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0}, F_{t_1}(y^{t_1}) - F_{t_0}(y^{t_0}) > \delta)}{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0})} \quad k, l = 1, \dots, K, \quad (3)$$

where $F_t(y^t)$ denotes the marginal distribution of y in period t and $\delta \in [0, 1 - F_0(\zeta_k^{t_0})]$ is a predefined constant representing the threshold defining upward mobility. In words, (3) captures the probability of an individual exceeding his or her initial percentile in the terminal period by at least δ conditional on being located between $\zeta_{k-1}^{t_0}$ and $\zeta_k^{t_0}$ in the initial period. The corresponding measure of downward mobility is given by

$$\varpi_{kl}^{t_0, t_1} = \frac{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0}, F_{t_1}(y^{t_1}) - F_{t_0}(y^{t_0}) < -\delta)}{\Pr(\zeta_{k-1}^{t_0} \leq y^{t_0} < \zeta_k^{t_0})}, \quad (4)$$

where $\delta \in [0, F_{t_0}(\zeta_{k-1}^{t_0})]$. In words, (4) captures the probability of an individual reducing his or her initial percentile in the terminal period by at least δ conditional on being located between $\zeta_{k-1}^{t_0}$ and $\zeta_k^{t_0}$ in the initial period. Finally, we can compute *conditional* measures of upward and downward mobility by conditioning on $X = x$.

⁸For example, if $K = 10$, then the cutoff points might correspond to deciles within the two marginal distributions of y^{t_0} and y^{t_1} .

While transition matrices, and the corresponding measures of upward and downward mobility, have the advantage of discretizing the continuous CDF, $F_{t_0, t_1}(y^{t_0}, y^{t_1})$, they may not yield unambiguous rankings of the degree of mobility across different samples (e.g., comparing P_{t_0, t_1} across whites and non-whites or comparing P_{t_0, t_1} to P_{t_1, t_2}). Consequently, several summary measures have been proposed. A summary measure is a function, $M(P_{t_0, t_1})$, which maps the transition matrix into a scalar such that one transition matrix, P , is said to represent greater mobility than an alternative transition matrix, \tilde{P} , if $M(P) > M(\tilde{P})$. Assuming the cutoff points are chosen such that $\Pr(\zeta_{k-1}^s \leq y^s < \zeta_k^s) = 1/K \forall k, s$, then the summary measures considered here are

(M1) Prais (1955):

$$M(P) = \frac{K - \text{trace}(P)}{K}$$

(M2) Bartholomew (1982):

$$M(P) = \frac{1}{K(K-2)} \sum_{k=1}^K \sum_{l=1}^K p_{kl} |k - l|.$$

(M3) $-\chi^2$:

$$M(P) = -K \sum_{k=1}^K \sum_{l=1}^K [p_{kl} - (1/K)]^2.$$

The Prais (1955) measure reflects the average probability that a child is in a different weight class in period t_1 than in period t_0 (Formby et al. 2004); we normalize the measure to be bounded between zero and one (Buchinsky and Hunt 1999). The Bartholomew (1982) measure is the average number of weight classes crossed by all children (Formby et al. 2004); again, we normalize the measure to be bounded between zero and one (Buchinsky and Hunt 1999). Finally, the $-\chi^2$ measure is increasing in the deviation between the transition matrix and the expected transition matrix under time independence (i.e., the matrix with all elements equal to $p_{kl} = 1/K$) (Fields 2000). Thus, whereas the Prais (1955) measure is only concerned with the diagonal elements of the transition matrix, the latter three measures also take into account the distance moved by children across time periods. However, all three measures capture *relative* mobility only; absolute changes in weight outcomes alone do not show up as mobility.

The remaining measures utilized here are not based on the computation of an underlying transition matrix *per se*. Two straightforward measures are based on correlations between child weight in periods t_0 and t_1 . The first uses the traditional Pearson correlation coefficient, while the second uses the rank correlation coefficient. Upon computation of each correlation coefficient, the measures of mobility are given by

(M4) Correlation:

$$M(\rho) = 1 - \rho.$$

Thus, higher values continue to be associated with greater mobility as ρ equals zero in both cases when the data are time independent (Fields 2000).⁹ As with the prior measures, the correlation-based measures also capture only relative mobility.

⁹More generally, mobility measures of the form $M = 1 - \rho(f(y^{t_0}), f(y^{t_1}))$, where $f(\cdot)$ is a function such that $f'(\cdot) > 0$, have appeared in the literature. Other examples include the Hart (1981) index, where $f(y^t) = \ln(y^t)$, and an exponential family, where $f(y^t) = (y^t)^a$, $a > 0$.

The next two measures are based on the notion that, with greater mobility, outcomes aggregated over multiple periods should be more equal than outcomes from the initial period (or any individual period). Formally, these measures are given by

(M5) Shorrocks (1978):

$$M_S = 1 - \frac{I(\bar{y})}{\frac{1}{t_1 - t_0 - 1} \sum_{t=t_0}^{t_1} \frac{\mu^t}{\mu^{t_0, t_1}} I(y^t)}$$

where $I(\cdot)$ is some measure of inequality, \bar{y} is a vector of child-specific outcomes averaged over the periods t_0 to t_1 , μ^t is the mean outcome in period t , and μ^{t_0, t_1} is the mean outcome over the entire period spanning from t_0 to t_1

(M6) Fields (2010):

$$M_F = 1 - \frac{I(\bar{y})}{I(y^{t_0})}.$$

Field's (2010) index is similar to Shorrocks' (1978), but replaces the denominator with inequality computed only in the initial period. In contrast to Field's (2010) index, Shorrocks' (1978) index has the property of treating equalizing and disequalizing changes in nearly an identical manner (Fields 2010). Both measures may reflect absolute as well as relative mobility depending on the inequality measure used.

The final two measures come from Cowell and Flachaire (2011). Both measures can be expressed as

(M7) Cowell and Flachaire (2011):

$$M_{CF}^\alpha = \begin{cases} \frac{1}{\alpha(\alpha-1)} \left[\frac{\frac{1}{N} \sum_i (x_i^{t_0})^\alpha (x_i^{t_1})^{1-\alpha}}{(\mu^{t_0})^\alpha (\mu^{t_1})^{1-\alpha}} - 1 \right] & \alpha \neq 0, 1 \\ \frac{\frac{1}{N} \sum_i x_i^{t_1} \log(x_i^{t_1}) - \frac{1}{N} \sum_i x_i^{t_1} \log(x_i^{t_0})}{\mu^{t_1}} + \log\left(\frac{\mu^{t_0}}{\mu^{t_1}}\right) & \alpha = 0 \\ \frac{\frac{1}{N} \sum_i x_i^{t_0} \log(x_i^{t_0}) - \frac{1}{N} \sum_i x_i^{t_0} \log(x_i^{t_1})}{\mu^{t_0}} + \log\left(\frac{\mu^{t_1}}{\mu^{t_0}}\right) & \alpha = 1 \end{cases}$$

where a large, positive (negative) value of α produces an index that is particularly sensitive to downward (upward) movements (Cowell and Flachaire 2011).

To operationalize M_{CF}^α for a given value of α , x^{t_0} and x^{t_1} must be defined. In the first case, $x_i^s = y_i^s$, $s = 1, \dots, T$. In the second case, $x_i^s = F_s(y_i^s)$, where $F_s(\cdot)$ is the marginal CDF of y^s , $s = 1, \dots, T$. Cowell and Flachaire (2011) refer to the second case as capturing rank (relative) mobility; the first case measures absolute and relative mobility. In practice, this second measure is implemented by replacing $F_s(\cdot)$ with its empirical counterpart, defined as

$$\hat{F}_s(y) = \frac{1}{N} \sum_i \mathbf{I}(y_i^s \leq y) \quad (5)$$

where $\mathbf{I}(\cdot)$ is the indicator function.

3.2 Regression Approach to Persistence Measurement

The nonparametric approach discussed above offers the advantage of not requiring one to model how weight status is determined in each period. Alternatively, persistence – and, more importantly, the various components of persistence – may be assessed within a dynamic regression approach. At the cost of placing greater structure on the evolution

of child weight, the regression approach has the advantage of allowing persistence to be decomposed into various components reflecting state dependence, observed heterogeneity, and unobserved heterogeneity.

The simplest estimating equation is

$$y_{it} = \gamma y_{it-1} + \varepsilon_{it}, \quad i = 1, \dots, N; \quad t = 1, \dots, T \quad (6)$$

where y_{it} is a measure of weight status for child i at time t , ε_{it} is a mean zero error term, and T must be at least two (given observability of the initial observation, y_{i0}). Here, γ reflects the overall level of persistence as it captures the entire association between past and current weight status. To decompose this overall persistence, we next incorporate *observed* heterogeneity into the model

$$y_{it} = \gamma y_{it-1} + x_{it}\beta + w_i\delta + \varepsilon_{it}, \quad i = 1, \dots, N; \quad t = 1, \dots, T \quad (7)$$

where x_{it} is a vector of observed, time-varying attributes of child i at time t and w_i is a vector of observed, time invariant attributes of child i . The change in the estimate of γ from (6) to (7) reflects the portion of persistence attributable to persistent, observed heterogeneity. Finally, we include observed time-varying heterogeneity and all sources (observed and unobserved) of time-invariant heterogeneity into the model

$$y_{it} = \gamma y_{it-1} + x_{it}\beta + \alpha_i + \varepsilon_{it}, \quad i = 1, \dots, N; \quad t = 1, \dots, T \quad (8)$$

where α_i is a child-specific fixed effect. In (8) γ reflects the degree of *state dependence* as it captures the causal effect of past weight status on current weight status. The child-specific fixed effect, α , reflects persistence in child weight status due to persistent observed and unobserved, child-specific heterogeneity (such as time invariant environmental and genetic factors). In such models, β represents the contemporaneous effects of the observed, time varying regressors, whereas $\beta/(1 - \gamma)$ represents the long-run effects of a permanent unit change in these variables.

Estimation of (8) is straightforward (assuming the model is correctly specified). Following Anderson and Hsiao (1981), (8) is first-differenced to eliminate α_i . The first-differenced model is then estimated via instrumental variables since the first-differenced lagged dependent variable is necessarily correlated with the first-differenced error term. However, y_{it-2} represents a valid instrument if ε is serially uncorrelated. The models are estimated by Generalized Method of Moments (GMM).

Once the models are estimated, in addition to simply examining the coefficient estimates, we follow the logic in Ulrick (2008) and simulate probabilities such as the following

$$\Pr(y_{iT} \geq y^* | y_{i0} \geq y_0) \quad (9)$$

given estimates of the regression model. Here, (9) represents the probability of a child having a weight status above y^* in the terminal period conditional on an initial weight status greater than or equal to some value y_0 . For example, one might be interested in the probability of a child having a BMI above the 85th percentile in period T conditional on being above the 85th percentile in the initial period, $t = 0$. These probabilities incorporate not just the coefficient directly related to persistence, γ , but also reflect persistence due to persistence in observed and unobserved determinants of child weight. Moreover, by altering the attributes of individuals, we can simulate counterfactual

probabilities as well. Finally, we can also simulate these probabilities and counterfactual probabilities for different sub-samples conditional on particular attributes. This allows one to determine if the degree of persistence, and the factors contributing to such persistence, vary across socioeconomic groups.

Before detailing the simulations undertaken, note that upon estimating (8), estimates of α_i are given by

$$\hat{\alpha}_i = \frac{1}{T} \sum_{t=1}^T \left[y_{it} - \hat{\gamma} y_{it-1} - x_{it} \hat{\beta} \right], \quad i = 1, \dots, N. \quad (10)$$

The estimates can then be decomposed into observed and unobserved time invariant factors by estimating the following model using OLS

$$\hat{\alpha}_i = w_i \delta + \eta_i, \quad (11)$$

where w_i now includes an intercept and η is a mean zero error term. Finally, given estimates of γ , β , and α , we can obtain estimates of the idiosyncratic errors, ε and η , using (8) and (11).

To proceed, we simulate the following probabilities:

1. Own y_{i0} , own x_{it} , set $\varepsilon_{it} = 0$, and
 - (a) replace $\alpha_i = \bar{\alpha}$, or
 - (b) draw $\alpha_i \sim F(\alpha)$ where $F(\cdot)$ is the empirical distribution of α_i , or
 - (c) draw $\alpha_i \sim F_G(\alpha)$ where $F_G(\cdot)$ is the empirical distribution of α_i in sub-sample G and $i \in G$, or
 - (d) draw $\alpha_i \sim F_{G'}(\alpha)$ where $F_{G'}(\cdot)$ is the empirical distribution of α_i in sub-sample G' and $i \notin G'$.
2. Own y_{i0} , own x_{it} , set $\eta_i = 0$, set $\varepsilon_{it} = 0$, and
 - (a) own w_i , or
 - (b) draw $w_i \sim F(w)$ where $F(\cdot)$ is the empirical distribution of w_i , or
 - (c) draw $w_i \sim F_G(w)$ where $F_G(\cdot)$ is the empirical distribution of w_i in sub-sample G and $i \in G$, or
 - (d) $w_i \sim F_{G'}(w)$ where $F_{G'}(\cdot)$ is the empirical distribution of w_i in sub-sample G' and $i \notin G$.
3. Own y_{i0} , own x_{it} , own w_i , set $\varepsilon_{it} = 0$, and
 - (a) draw $\eta_i \sim F(\eta)$ where $F(\cdot)$ is the empirical distribution of η_i , or
 - (b) draw $\eta_i \sim F_G(\eta)$ where $F_G(\cdot)$ is the empirical distribution of η_i in sub-sample G and $i \in G$, or
 - (c) draw $\eta_i \sim F_{G'}(\eta)$ where $F_{G'}(\cdot)$ is the empirical distribution of η_i in sub-sample G' and $i \notin G$.
4. Own y_{i0} , own α_i , set $\varepsilon_{it} = 0$, and
 - (a) replace $x_{it} = \bar{x}_t$, or
 - (b) draw $x_{it} \sim F(x_1, \dots, x_T)$ where $F(\cdot)$ is the empirical joint distribution of x_1, \dots, x_T , or
 - (c) draw $x_{it} \sim F_G(x_1, \dots, x_T)$ where $F_G(\cdot)$ is the empirical joint distribution of x_1, \dots, x_T in sub-sample G and $i \in G$, or.

- (d) draw $x_i. \sim F_G(x_1, \dots, x_T)$ where $F_G(\cdot)$ is the empirical joint distribution of x_1, \dots, x_T in sub-sample G and $i \in G$.

5. Own y_{i0} , own x_{it} , own α_i , and

- (a) draw $\varepsilon_i. \sim F(\varepsilon_1, \dots, \varepsilon_T)$ where $F(\cdot)$ is the empirical distribution of $\varepsilon_i.$, or
(b) draw $\varepsilon_i. \sim F_G(\varepsilon_1, \dots, \varepsilon_T)$ where $F_G(\cdot)$ is the empirical distribution of $\varepsilon_i.$ in sub-sample G and $i \in G$, or
(c) draw $\varepsilon_i. \sim F_{G'}(\varepsilon_1, \dots, \varepsilon_T)$ where $F_{G'}(\cdot)$ is the empirical distribution of $\varepsilon_i.$ in sub-sample G' and $i \notin G$.

6. Own y_{i0} , own α_i , and

- (a) draw $x_i., \varepsilon_i. \sim F(x_1, \dots, x_T, \varepsilon_1, \dots, \varepsilon_T)$ where $F(\cdot)$ is the empirical joint distribution of $x_1, \dots, x_T, \varepsilon_1, \dots, \varepsilon_T$,
or
(b) draw $x_i., \varepsilon_i. \sim F_G(x_1, \dots, x_T, \varepsilon_1, \dots, \varepsilon_T)$ where $F_G(\cdot)$ is the empirical joint distribution of $x_1, \dots, x_T, \varepsilon_1, \dots, \varepsilon_T$ in sub-sample G and $i \in G$, or
(c) draw $x_i., \varepsilon_i. \sim F_{G'}(x_1, \dots, x_T, \varepsilon_1, \dots, \varepsilon_T)$ where $F_{G'}(\cdot)$ is the empirical joint distribution of $x_1, \dots, x_T, \varepsilon_1, \dots, \varepsilon_T$ in sub-sample G' and $i \notin G$.

See the Appendix for further details.¹⁰

Case 1 eliminates time-varying, unobserved heterogeneity, ε_{it} , and assesses the impact of altering the distribution of time invariant heterogeneity, α_i . Case 1a eliminates all time invariant heterogeneity. Cases 1b – 1d replace actual time invariant heterogeneity with a random draw. Case 1b draws from the population empirical distribution. Case 1c draws from the empirical distribution of the same sub-group as observation i . Case 1d draws from the empirical distribution of the sub-group to which observation i does not belong. For example, if we divide the sample based on gender, Case 1c draws a value of α from the empirical distribution of boys for each boy. Case 1d entails drawing a value of α from the empirical distribution of girls for each boy. Case 1b succeeds in entirely breaking any correlation between the initial condition, y_{i0} , and x_{it} and time invariant heterogeneity, α_i . Case 1c partially breaks this correlation. In total, these cases speak to the relative importance of time invariant heterogeneity in the persistence of weight status, as well as differences in the distribution of α across different sub-groups.

Case 2 continues to eliminate time-varying, unobserved heterogeneity, ε_{it} . However, time invariant, unobserved heterogeneity, η_i , is now also eliminated; the observed component of time invariant heterogeneity is then altered. Case 2a utilizes each observation's own time invariant heterogeneity, w_i . Case 2b draws w_i from the population empirical distribution. Case 2c draws w_i from the empirical distribution of the same sub-group as observation i . Case 2d draws w_i from the empirical distribution of the sub-group to which observation i does not belong. Case 3 is similar, but has individuals retain their time invariant, observed heterogeneity, w_i , and alters the values of time invariant, unobserved heterogeneity, η_i . Case 3a draws η_i from the population empirical distribution. Case 3b draws η_i from the empirical distribution of the same sub-group as observation i . Case 3c draws η_i from the empirical distribution of the sub-group to which observation i does not belong. Altogether, Cases 2 and 3 permit assessment of the relative

¹⁰ Appendix is available at http://faculty.smu.edu/millimet/pdf/usda_ccr_appendix.pdf.

importance of the observed and unobserved components of time invariant heterogeneity in the persistence of weight status. Moreover, they will also illuminate any salient differences in these components across different sub-groups.

Case 4 continues to eliminate time-varying, unobserved heterogeneity, ε_{it} , and assesses the impact of altering the distribution of time-varying, observed heterogeneity, x_{it} . Case 4a eliminates all time-varying heterogeneity. Cases 4b – 4d replace actual time-varying, observed heterogeneity with a random draw. Case 4b draws from the population empirical distribution. Case 4c draws from the empirical distribution of the same sub-group as observation i . Case 4d draws from the empirical distribution of the sub-group to which observation i does not belong. Case 4b succeeds in entirely breaking any correlation between the initial condition, y_{i0} , and α_i and time-varying, observed heterogeneity, x_{it} . Case 4c partially breaks this correlation. These cases complement the simulations performed in Case 1 as they speak to the relative importance of time-varying, observed heterogeneity in the persistence of weight status, as well as differences in the distribution of x across different sub-groups.

Case 5 has individuals retain their time-varying, observed attributes, x_{it} , and time invariant attributes, α_i and y_{i0} , but alters the value of time-varying, unobserved heterogeneity, ε_{it} . Case 5a draws ε_{it} from the population empirical distribution. Case 5b draws ε_{it} from the empirical distribution of the same sub-group as observation i . Case 5c draws ε_{it} from the empirical distribution of the sub-group to which observation i does not belong. Finally, Case 6 has individuals only retain their time invariant attributes, α_i and y_{i0} . All time-varying heterogeneity is sampled. Case 6a draws x_{it} and ε_{it} from the population empirical distribution. Case 6b draws x_{it} and ε_{it} from the empirical distribution of the same sub-group as observation i . Case 6c draws x_{it} and ε_{it} from the empirical distribution of the sub-group to which observation i does not belong. Thus, these final two cases address the relative importance of the observed and unobserved components of time-varying heterogeneity in the persistence of weight status. The results will also highlight any important differences in these components across different sub-groups.

4 Data

In the initial analysis, we utilize data from the restricted version of the ECLS-K. Collected by the US Department of Education, the ECLS-K surveys a nationally representative cohort of children throughout the US in fall and spring kindergarten, fall and spring first grade, spring third grade, spring fifth grade, and spring eighth grade.¹¹ The sample includes data on over 20,000 students who entered kindergarten in one of roughly 1,000 schools during the 1998-99 school year. In addition to family background information, height and weight measures are available from children in each round, as well as information on birth weight.

Our final sample consists of children for whom we have valid measures of age, gender, height, and weight.¹² From the information on height and weight of the children, we create a number of outcome measures: weight z -scores

¹¹The survey design is troublesome in that the ECLS-K contains irregularly spaced waves. To minimize the issue, we omit the spring kindergarten and fall first grade waves and thus each period conceptually represents roughly a two-year window.

¹²The initial sample size of the ECLS-K is 21,260. After cleaning age, weight, and height as described in Millimet and Tchernis (2012, Appendix C), and due to sample attrition, the sample size falls to 9,360 in the final wave of the data. Restricting the sample to a balanced panel reduces the sample size to approximately 9,160. This is the final sample size per wave in the regression analysis. For the nonparametric mobility analysis, we further restrict the sample to those with available data on birthweight. This reduces the sample size per wave to roughly 8,370. Note, all sample sizes are rounded to the nearest 10 per NCES restricted data regulations.

and corresponding percentiles, height z -scores and corresponding percentiles, and BMI z -scores and corresponding percentiles. Note that z -scores and percentiles are based on CDC 2000 growth charts; these are age- and gender-specific, are adjusted for normal growth, and percentiles are based on the underlying reference population.¹³ When assessing mobility using transition matrices, the choice of using z -scores or percentiles is irrelevant since one is simply a monotonic transformation of the other. However, when computing our nonparametric measures of mobility, we focus on the percentile outcomes since these are strictly positive (which is required for mobility measures utilizing inequality metrics that require non-negative values). In our regression models, we focus on the three z -score variables since these avoid issues associated with bounded outcomes. Finally, note that we present results for weight alone since mobility in terms of height over the age ranges we examine is most likely due to differential timing in the onset of puberty, which is at least in part driven by nutrition (Herman-Giddens 2006).

Data on family background are used in two different manners in the analysis. First, we define different demographic groups in order to split the sample during the nonparametric measurement of mobility, as well as during the probability simulations based on the regression analysis. Here, we consider five different partitions based on race (white vs. non-white), gender (male vs. female), urban status (urban vs. rural/suburban), mother’s education (college vs. less than college), and socioeconomic status (low vs. high SES). Second, we incorporate time-varying, x_{it} , and time invariant, w_i , attributes into the regression model.

The following time invariant covariates are included: gender, race/ethnicity (white, black, Hispanic, Asian, and other), birthweight, indicator for premature birth, indicator for being born in the U.S., indicator for being a native English speaker, city type (urban, suburban, or rural), region (northeast, midwest, south, and west), mother’s education (less than high school, high school/GED, some college, four-year college degree, and more than four years of college), mother’s age at first birth, mother’s marital status at birth, indicator for nonparental pre-kindergarten (i.e., cared for by a relative or nonrelative or in a Head Start or other pre-kindergarten program), indicator for mother’s labor force participation during infancy, indicator for mother’s participation in WIC (Women’s, Infants, and Children) during pregnancy, indicator for mother’s participation in WIC during infancy, indicator for mother’s participation in TANF (Temporary Assistance for Needy Families) during infancy, indicator for participation in FSP (Food Stamp Program) during infancy, and indicator for attending full day kindergarten.¹⁴ The following time-varying covariates are included: an index of SES status, indicator for the household being in poverty, number of children’s books in the household, household size, family type (two parents plus siblings, two parents and no siblings, one parent and siblings, one parent and no siblings, and other), mother’s labor force status (full-time, part-time, and not working), indicator for mother absent from the household, indicator of current TANF participation, indicator of current FSP participation, indicator for health insurance, hours spent watching television during the school week, hours spent watching television during the weekend, indicator for household rules regarding television watching, days per week household eats breakfast together, days per week household eats dinner together, indicator for household food security (household never worried about running out of food), neighborhood safety (very safe, somewhat safe, and not safe), and percent of minority students in class at school. For all covariates (except gender, age, height, and

¹³ z -scores and their percentiles are obtained using the `-zanthro-` command in Stata.

¹⁴ FSP was renamed the Supplemental Nutrition Assistance Program (SNAP) in October 2008. Since the data pre-dates this change, we refer to the program as FSP.

weight), we include dummy variables for missing observations.

5 Results

5.1 Nonparametric Analysis

Transition Matrices Tables 1a – 1c display transition matrices for the balanced sample of children with valid measures of birthweight and weight and height in fall kindergarten, spring first grade, spring third grade, spring fifth grade, and spring eighth grade. The tables examine percentile weight, percentile height and BMI percentile, respectively. Recall, the percentile outcomes are based on the underlying reference population used in the CDC 2000 growth charts, *not* the current sample. The transition matrices span the period from fall kindergarten to spring eighth grade.¹⁵ In all cases, $K = 5$ and thus the matrices capture movements across quintiles.¹⁶ Finally, note that within each table we present results for the full sample, as well as the sample divided by race (white vs. non-white), gender (male vs. female), urban status (urban vs. rural/suburban), mother’s education (college vs. less than college), and socioeconomic status (low vs. high SES). We also present a test of equality of the transition matrices across these divisions (e.g., Tan and Yilmaz 2002).

Turning to the results for the full sample, three findings stand out. First, the conditional staying probabilities are highest in the extremes of the distribution. Specifically, for all measures, the conditional staying probability for quintile one (five) varies from 0.45 to 0.61 (0.59 to 0.61), whereas the conditional staying probabilities for the second through fourth quintiles are typically around 0.30. Thus, children in the tails of the distribution are likely to remain there; mobility is concentrated within the middle of the distribution. Second, the outcome that incorporates both height and weight (BMI in Table 1c) exhibits more mobility, particularly in the lower tail of the distribution, than measures based solely on height or weight. For example, the probability of staying in the bottom quintile drops from 0.61 when using percentile height to 0.45 when using percentile BMI. Moreover, for those in the lowest quintile of the distribution according to percentile BMI (percentile weight) in fall kindergarten, the probability of being in one of the highest three quintiles in spring eighth grade is 0.29 (0.22). And, while for those in the highest quintile of the distribution according to percentile BMI (percentile weight) in fall kindergarten, the probability of being in one of the lowest three quintiles in spring eighth grade is 0.15 (0.12). Finally, the probability of staying in the top quintile is remarkably stable (0.59 to 0.61) regardless of the measure used.

Examining the results for different demographic groups, a few additional findings emerge. First, the most robust, statistically meaningful difference arises across racial groups. For all outcomes except percentile height, the transition matrices for white and non-white children are statistically different at the $p \leq 0.01$ confidence level. For these outcomes, the diagonal elements (representing the conditional staying probabilities) are always higher for non-whites. This is suggestive of greater persistence in kindergarten weight status for minorities. Second, the transition matrices for percentile weight are statistically different by gender at the $p \leq 0.05$ confidence level. In this case, the conditional

¹⁵Table B1 in Appendix B present more detailed transition matrices for percentile weight, spanning the periods (i) birth through spring eighth grade, (ii) birth through fall kindergarten, and (iii) fall kindergarten through spring eighth grade.

¹⁶Note, the quintiles in the transition matrices refers to quintiles of *our* sample, not quintiles of the underlying distributions used to compute the percentile weight and height measures.

staying probabilities are larger for females except in the fifth quintile, which means that girls have higher probability of staying in the same quintile if they start in the first four quintiles, but boys have higher staying probability in the top quintile. Third, there are a few cases where the transition matrices are statistically different across mother’s education status and household SES status; there are no statistically meaningful differences by urban status. Strikingly, for both education and SES status, the conditional staying probabilities in the *tails* of the distribution tend to be higher in households with less educated mothers and lower overall SES status (similar to racial differences); these groups exhibit more movement in the middle of the distribution. Finally, as shown in Appendix B (Table B1), there is much greater mobility from birth through entry into kindergarten than kindergarten through eighth grade. This is perhaps not surprising as infants at risk of being underweight or obese in the future are drawn more or less equally from infants with extreme low or high birthweight.

Summary Mobility Measures Tables 2a – 2c display the summary mobility measures for each of the same three outcomes and various sub-samples. Each table presents five mobility measures: Bartholomew’s (1982) measure, Spearman rank correlation measure, Shorrocks’ (1978) measures using the Theil index to measure inequality, and Cowell and Flaichaire’s (2011) measures based on absolute and rank values of the outcomes with $\alpha = 0.17$. Recall, for all measures, higher values correspond to greater mobility. Standard errors are shown based on 250 bootstrap repetitions, clustered at the child-level. Finally, we report the mobility measures over several time periods, including the full sample period from fall kindergarten through spring eighth grade as well as the sub-periods from fall kindergarten through spring first grade, spring first grade through spring third grade, spring third grade through spring fifth grade, and spring fifth grade through spring eighth grade.

In terms of the full sample results, two findings stand out. First, the various measures generally agree as it relates to changes in the degree of mobility across time periods. Second, for percentile weight and BMI, there exists a clear pattern: mobility follows a *U*-shaped pattern, being greatest between fall kindergarten and spring first grade and spring fifth and eighth grades and lowest between spring third and fifth grades.¹⁸ For example, using Shorrocks’ (1978) measure and percentile BMI, mobility is 0.437 over the period spanning fall kindergarten to spring first grade, 0.313 over the period spanning spring first to spring third grade, 0.170 over the period spanning spring third to spring fifth grade, and 0.230 over the period spanning spring fifth to spring eighth grade (see Table 2c). Given the structure of schooling faced by most children in the U.S., this suggests that mobility is highest during times of transition (i.e., at the start of primary school and then again at the start of middle school). This timing also coincides with two of the three ‘critical’ periods for the onset of childhood obesity; namely, the period of so-called adiposity rebound, typically occurring between ages four and six, and the transition into adolescence (Dietz 1997).^{19,20} Moreover, the higher mobility between fall kindergarten and spring first grade as compared with between spring fifth and eighth grade is consistent with the period of adiposity rebound being of greater importance. In terms of policy advice, this suggests

¹⁷Tables B2a – B2c in Appendix B present additional mobility measures described in Section 3.1, as well as computations of the mobility measures using birth outcomes as one of the time periods when analyzing weight.

¹⁸In part this could be driven by the larger interval between the final two waves of the survey. Thus, future research with alternative data sources is needed to confirm the robustness of this finding.

¹⁹Adiposity rebound denotes the period where the CDC growth charts reach a minimum and then being increasing.

²⁰The third critical period is the prenatal period, discussed at great length later.

that interventions during times of transition to a new school, particularly elementary school, are potentially more effective as children develop new routines within their new environment coinciding with critical stages of biological development.

Turning to the results for different demographic groups, three results emerge. First, as with the full sample, the different mobility measures generally agree as it relates to changes in mobility across time periods. Moreover, they also generally agree on the relative mobility of the different demographic groups. Second, for each demographic group, the *U*-shaped pattern noted in the full sample continues to appear; mobility is greater at the start of kindergarten than the transition to middle school. Finally, among the different groups, mobility in terms of the weight outcomes is generally *lower* over the full sample period (fall kindergarten through spring eighth grade), as well as over different sub-periods, for non-whites relative to whites and urban relative to non-urban residents. There is little robust difference when dividing the sample by mother’s education or household SES status. When splitting the sample by gender, an interesting pattern is found; girls have lower mobility over the entire sample period and during early elementary school, but higher mobility during middle school. For height, mobility is predominantly *greater* for non-whites relative to whites, girls relative to boys, and urban relative to non-urban residents. For gender, the greater mobility for girls is presumably due to variation in the onset of puberty, which may begin earlier for girls than boys (Herman-Giddens 2006). It is also consistent with the period of transition into adolescence being of greater biological significance in girls.

Upward Mobility Tables 3a – 3c present the estimates of upward mobility based on (3). Specifically, conditional on being in a given quintile in the initial period, the measure represents the probability of a child moving up at least ten percentile points in the distribution in the terminal period (i.e., $\delta = 0.10$). Standard errors are shown based on 250 bootstrap repetitions, clustered at the child-level. As with the summary mobility measures, we report the upward mobility measures over several time periods, including the full sample period from fall kindergarten through spring eighth grade as well as the sub-periods from fall kindergarten through spring first grade, spring first grade through spring third grade, spring third grade through spring fifth grade, and spring fifth grade through spring eighth grade.²¹

In terms of the full sample, three patterns are noticeable. First, except for percentile height, there is a negative, monotonic relationship across the quintiles when examining the full sample period (from fall kindergarten to spring eighth grade). For example, the probability of moving up at least ten percentile points in the distribution of percentile BMI is 0.543 for children initially in the first quintile, 0.409 for the second quintile, 0.311 for the third quintile, 0.189 for the fourth quintile, and 0.032 for the top quintile (see Table 3c). While it is understandable that upward mobility is lowest for children initially in the fifth quintile (since only those below the 90th percentile have the ability to move up at least ten percentile points), there is nothing that guarantees that upward mobility must lower as one moves up the distribution in the initial period. For percentile height, upward mobility is higher in the second quintile than the first. Second, despite upward mobility becoming monotonically smaller across the initial distribution when

²¹ Tables B3a – B3c in Appendix B also present estimates of the probability of moving up at all in the distribution (i.e., $\delta = 0$), as well as computations of upward mobility using birth outcomes as one of the time periods. Figures C1, C3, and C5 in Appendix C present a subset of the results graphically.

examining the full sample period, when we assess upward mobility across different sub-periods, we find it is greatest for those initially in the second quintile for percentile weight and percentile height. For percentile BMI, upward mobility is greatest for those initially in the first quintile during early primary school and greatest for those initially in the second quintile during later primary and middle school.

Finally, for percentile weight and BMI, we continue to find strong evidence of a *U*-shaped relationship in mobility across time periods, consistent with the ‘critical’ periods of child development discussed earlier. In particular, for most quintiles and outcomes (and for all quintiles when examining percentile BMI), upward mobility is lowest over the period spanning spring third to spring fifth grades. For example, the probability of moving up at least ten percentile points in the distribution of percentile BMI for a child in the lowest quintile in the initial period is 0.380 over the period spanning fall kindergarten to spring first grade, 0.329 over the period spanning spring first to spring third grade, 0.224 over the period spanning spring third to spring fifth grade, and 0.292 over the period spanning spring fifth to spring eighth grade (see Table 3c). Thus, children in this category are nearly twice as upwardly mobile at the start of elementary school than during the middle years of elementary school. As noted previously, the fact that upward mobility tends to be the greatest at the start of kindergarten and then over the period most likely encompassing the start of middle school suggests that interventions aligned with transitions in schooling, which also coincide with critical periods of biological development, may achieve greater success. For percentile height, upward mobility is fairly constant across primary school and then becomes much greater over the period spanning spring fifth to spring eighth grades. Again, this is consistent with significant variation in the timing of the onset of puberty across children.

Turning to the results for different demographic groups, three results emerge. First, for each demographic group, the negative, monotonic relationship across the quintiles when examining the full sample period continues to hold. The *U*-shaped pattern across the different sub-periods noted in the full sample also continues to appear in the vast majority of cases. Second, across the different demographic groups, there are not many strong differences. Perhaps the most noticeable pattern we discern is that whites relative to non-whites, males relative to females, and urban relative to non-urban residents tend to have greater upward mobility over the full sample period when assessing percentile weight and height. However, when examining percentile BMI, only the greater upward mobility for whites relative to non-whites tends to remain. Another pattern that appears is that upward mobility is greater for children with college educated mothers when examining percentile weight and BMI.

Downward Mobility Tables 4a – 4c present the final set of nonparametric mobility estimates, those of downward mobility based on (4). Specifically, conditional on being in a given quintile in the initial period, the measure gives the probability of a child moving down at least ten percentile points in the distribution in the terminal period (i.e., $\delta = 0.10$). Standard errors are shown based on 250 bootstrap repetitions, clustered at the child-level. The estimates obtained mirror those for upward mobility given in Tables 3a – 3c.²²

In terms of the full sample, three patterns are noticeable. First, except for percentile height, there is an inverted

²²Tables B4a – B4c in Appendix B also mirror Tables B3a – B3c, containing estimates of the probability of moving down at all in the distribution (i.e., $\delta = 0$), as well as computations of downward mobility using birth outcomes as one of the time periods. Figures C2, C4, and C6 in Appendix C present a subset of the results graphically.

U-shaped relationship across the quintiles, peaking at the fourth quintile, when examining mobility from fall kindergarten to spring eighth grade. For example, the probability of moving down at least ten percentile points in the distribution of percentile BMI is 0.052 for children initially in the first quintile, 0.311 for the second quintile, 0.417 for the third quintile, 0.513 for the fourth quintile, and 0.410 for the top quintile (see Table 4c). For percentile height, downward mobility displays a positive, monotonic pattern across the quintiles: 0.042 for children initially in the first quintile, 0.222 for the second quintile, 0.354 for the third quintile, 0.385 for the fourth quintile, and 0.398 for the top quintile (see Table 4b). Second, despite downward mobility peaking at the fourth quintile when examining weight outcomes over the full sample period, downward mobility tends to be largest at the third quintile when we examine different sub-periods. For percentile weight, downward mobility is greatest for those initially in the fourth quintile during early primary school and greatest for those initially in the third quintile during later primary and middle school. For percentile height, downward mobility is greater at the fourth quintile across the different sub-periods despite peaking at the fifth quintile over the full sample period.

Finally, as with the prior mobility measures, we find strong evidence of a *U*-shaped relationship in downward mobility across time periods for all outcomes. In particular, for most quintiles and outcomes, downward mobility is lowest over the period spanning spring third to spring fifth grades. For example, the probability of moving down at least ten percentile points in the distribution of percentile BMI for a child in the highest quintile in the initial period is 0.186 over the period spanning fall kindergarten to spring first grade, 0.117 over the period spanning spring first to spring third grade, 0.090 over the period spanning spring third to spring fifth grade, and 0.142 over the period spanning spring fifth to spring eighth grade (see Table 4c). Thus, children in this category are more than twice as downwardly mobile at the start of elementary school than during the middle years at elementary school. As stated above, the fact that downward mobility tends to be the greatest at the start of kindergarten and then over the period most likely spanning the start of middle school suggests that interventions coinciding with transitions in schooling, which also coincide with critical periods of biological development, are likely to have the greatest efficacy. For percentile height, downward mobility attains its minimum over the period spanning spring first through spring third grade for most quintiles, and is significantly greater over the period spanning spring fifth through spring eighth grades.

Turning to the results for different demographic groups, three results emerge. First, for each demographic group, the inverted *U*-shaped relationship across the quintiles, peaking at the fourth quintile, when examining the full sample period continues to hold for the weight outcomes. Moreover, this pattern also holds for many sub-groups when examining percentile height as well. In addition, the *U*-shaped pattern across the different sub-periods noted in the full sample continues to appear in the vast majority of cases, with the minimum downward mobility occurring typically over the period spanning spring third to spring fifth grades. Second, across the different demographic groups, there do not appear to many strong differences. Perhaps the most noticeable pattern we discern is that whites relative to non-whites and males relative to females tend to have greater downward mobility over the full sample period when assessing percentile weight and BMI. For percentile height, the most consistent differences arise in favor of greater downward mobility for children with college educated mothers and those residing in high SES households.

Discussion The analysis to this point generates much information. Stepping back to examine the big picture, we arrive at three main takeaway points. First, heterogeneity is very important. There is no universal measure of persistence or mobility; no single measure can capture the complex movements that occur throughout a given distribution over time. The analysis points to three primary sources of heterogeneity: initial quintile, age range, and demographic group. By initial quintile we mean that where a child starts in the distribution leads to differences in mobility patterns even conditional on the time period over which one is assessing mobility and conditional on the demographic group to which the child belongs. By age range we mean that mobility patterns vary depending over what time period one is assessing mobility even holding constant a child’s initial place in the distribution and demographic group. Finally, by demographic group, we mean that mobility patterns vary across demographic groups even conditional on a child’s initial place in the distribution and the time period. As discussed above, perhaps the most intriguing finding thus far is the relative amounts of mobility occurring at the start of primary school (i.e., between fall kindergarten and spring first grade) and between the final two waves in the data (i.e., spring fifth to spring eighth grade). Thus, interventions aimed at encouraging new, healthy behaviors are perhaps most likely to be effective when implemented during key transition periods such as entry into elementary and middle school, particularly when those transitions also coincide with evidence from the medical literature indicating these as critical periods of biological development.

Second, children from more disadvantaged households show less mobility and greater persistence in weight status. The greater persistence in BMI for more disadvantaged children holds regardless of whether we compare sub-populations based on race, mothers’ education, or SES. This suggests the potential for more disadvantaged children to be on an “obesity trajectory” earlier in life.

Third, when analyzing height and weight percentiles, we find greater upward mobility conditional on a child being initially in the second quintile than in the first quintile; the reverse is true for BMI. One would expect upward mobility in height, and to a lesser extent weight, to be greatest in the lower tail of the distribution. The fact that we do not see this pattern when examining weight and height individually suggests that there are important differences in the growth patterns for children who are particularly small; there is more persistence in the first quintile of the distribution of height and weight. However, this pattern disappears when weight and height are combined into a single BMI measure. A similar pattern also emerges when assessing downward mobility; there is more mobility in the fourth quintile than in the fifth for all three measures. These results suggest another important source of heterogeneity based on the measure of health status being examined. Specifically, the findings here suggest that researchers ought not concentrate solely on BMI, but also examine height and weight patterns individually.

5.2 Regression Analysis

Model Estimates Turning to the regression analysis allows us to further assess the overall level of persistence, as well as decompose the sources of such persistence. Tables 5 – 7 display the results from estimation of (6), (7), and (8) for three continuous outcomes: weight, height, and BMI z -scores.²³ Each estimation utilizes data from five waves:

²³Recall, the first specification, based on (6) does not control for any covariates. The second specification, based on (7) controls for observed time-invariant and time-varying covariates. The final specification, based on (8) includes time-varying observed covariates and

fall kindergarten, spring first grade, spring third grade, spring fifth grade, and spring eighth grade. The sample is a balanced panel of roughly 9,160 children.²⁴ In addition to reporting estimates of the coefficient on the lagged outcome, γ , we report the first-stage Kleibergen-Paap (2006) Wald rk F -statistic, the Kleibergen-Paap (2006) rk test of underidentification, and a test of endogeneity. The first two tests are designed to detect any issues associated with weak instruments. Finally, recall that within each sample (i.e., the overall sample of demographic sub-group), the estimate of γ from (6) reflects the overall level of persistence, the change in the estimate moving from (6) to (7) captures the portion of persistence explained by the observable covariates, and the change moving from (7) to (8) reflects the portion of persistence explained by time invariant, observed factors.

Table 5 displays the results for weight z -scores. For the full sample, the estimates of γ across the three specifications are 0.931, 0.932, and 0.775 (standard errors are 0.003, 0.003, and 0.067, respectively). Each is statistically significant at the $p \leq 0.01$ confidence level and all three specifications are strongly identified. The fact that the estimate of γ does not change moving from (6) to (7) implies that our lengthy vector of time-varying and time invariant observed factors explain none of the persistence in weight status for primary school-aged children. Moreover, the estimates of γ above 0.9 indicate a substantial degree of persistence. Thus, while persistence from one period to the next is extreme, this persistence is not attributable to or explained by characteristics typically observed by policymakers or health practitioners. Moving to the specification in (8), which replaces the time invariant observed factors with child-level fixed effects and thereby controls for all time invariant attributes of the child, the estimate of γ falls to 0.775, a decline of roughly 17% from 0.93. This implies that time invariant, *unobserved* factors explain about 17% of the observed persistence in weight z -scores. Examples of such factors include genetic endowments, prior health shocks determined *in utero* or during infancy, time invariant environmental factors such as the presence of grocery stores or outdoor amenities, etc.

When we divide the sample into different sub-groups, we find that the results are predominantly unchanged in the specifications omitting the fixed effects. The only minor difference we see is a slightly higher level of persistence for males relative to females (approximately 0.95 to 0.91, statistically significant at the $p \leq 0.01$ confidence level). However, once we include child-level fixed effects, the results vary in several cases. For whites, we find that time invariant, unobserved factors explain roughly 26% of overall persistence; only about 4% for non-whites. For males, the fixed effects explain over 70% of overall persistence as the estimate of γ falls to 0.276 (standard error is 0.056). For females, the point estimate on the lag dependent variable increases well above unity and is relatively imprecise. When splitting the sample by mother’s education, we find that time invariant, unobserved factors explain only 5% of total persistence for children with a college educated mother, but roughly 20% for those without a mother without a four-year college degree. Similarly, we find that the fixed effects explain about 4% of total persistence for urban residents, but roughly 23% for non-urban residents. Finally, we obtain little difference across groups when dividing the sample by SES status.

To interpret these findings, it is important to remember that the decline in γ when conditioning on the fixed effects represents the amount of persistence due to persistent unobserved risk factors. Consequently, we find that overall

fixed effects to control for all time-invariant attributes.

²⁴Sample sizes are rounded to the nearest 10 per NCES restricted data regulations.

persistence is fairly extreme as a one standard deviation in weight is associated with roughly a 0.9 standard deviation increase in the subsequent period. However, time-varying and time invariant observed attributes explain none of this persistence. Moreover, time invariant unobserved factors also explain very little of the persistence (typically less than one-third). Thus, much of the persistence in child weight is attributable to state dependence, which implies that early interventions that are successful in reducing child weight will have long-run effects. Unfortunately, since our covariates explain little of the variation in weight, identifying such early interventions may be difficult.²⁵

Table 6 displays the results for height z -scores. For the full sample, the estimates of γ across the first two specifications are very similar to those using weight z -scores; namely, 0.937 and 0.936 (standard errors are 0.004 and 0.004, respectively). However, the estimate of γ falls to 0.603 (standard error is 0.048) in the fixed effect specification (compared to 0.775 in Table 5). As in Table 5, the estimate of γ is statistically significant at the $p \leq 0.01$ confidence level, all three specifications are strongly identified, the estimate of γ barely changes when we include time-varying and time invariant observed attributes, and the estimates of γ above 0.9 in the first two specifications indicate a substantial degree of persistence. Thus, as in Table 5, while persistence from one period to the next in height z -scores is high, it is not attributable to or explained by observed characteristics.

In contrast to weight z -scores, the child-level fixed effects explain about 36% of the overall persistence in child height (versus only 17% for weight z -scores). This is perhaps not surprising as unobserved biological factors – most noticeably, parental height – are not included in our set of observed covariates. The fact that time invariant, unobserved attributes account for a greater share of the persistence in height implies that state dependence, and thus the long-run impact of successful, early interventions – that do not alter relevant, time invariant, unobserved attributes – is diminished. For example, a *one-time* intervention that reduces a child’s weight by one standard deviation prior to kindergarten entry, holding all else constant, is expected to reduce the child’s weight by over one-third a standard deviation in spring eighth grade. Thus, one-third of the effects of the early intervention persist through eighth grade. An intervention that raises a child’s height by one standard deviation prior to kindergarten entry, *ceteris paribus*, is expected to increase the child’s height by slightly over 0.10 standard deviations in spring eighth grade. As such, only about one-tenth of the effects of the early intervention persist through eighth grade; the remainder of the intervention dies out.

When we divide the sample into different sub-groups, we find that the results are predominantly unchanged in the specifications omitting the fixed effects. The only minor difference we see is a slightly higher level of persistence for males relative to females and non-urban residents relative to urban residents (approximately 0.95 to 0.92 and statistically significant at the $p \leq 0.01$ confidence level in each case). However, as with weight z -scores, once we include child-level fixed effects, the results vary in several cases. When we split the sample by race, we find that time invariant, unobserved factors explain roughly 41% of overall persistence for whites versus about 28% for non-whites. For males, the fixed effects explain over 50% of overall persistence as the estimate of γ falls to 0.460 (standard error

²⁵The full set of results are available upon request. While some estimated coefficients are statistically significant at conventional levels, the magnitudes are quite small; even the long-run effects of permanent changes in the covariates, given by $\beta/(1 - \gamma)$, are quite small. That said, while our covariate set does include a wide array of the usual family background variables, we do not have information on many recent interventions designed to combat obesity, such as education efforts, healthy food programs, and efforts to promote physical activity. We also do not have data on parents’ height or weight.

is 0.055). For females, the point estimate falls to 0.739 (standard error is 0.079); thus, accounting for only about 20% of overall persistence. When we divide the sample by mother’s education, we find that time invariant, unobserved factors also explain over 50% of total persistence for children with a college educated mother; roughly 30% for those with a mother without a four-year college degree. Similarly, we find that the fixed effects explain about 40% of total persistence for children in high SES households, but roughly 25% for children in low SES households. Finally, we obtain little difference across groups when dividing the sample by urban status.

Finally, Table 7 presents the results based on a simultaneous examination of persistence in weight and height through the analysis of BMI z -scores. For the full sample, the estimates of γ across the first two specifications are very similar to those in Tables 5 and 6; namely, 0.912 and 0.911 (standard errors are 0.004 and 0.005, respectively). However, the estimate of γ now falls to 0.217 (standard error is 0.015) in the fixed effect specification (compared to 0.775 and 0.603 in Tables 5 and 6, respectively). As in Tables 5 and 6, the estimate of γ is statistically significant at the $p \leq 0.01$ confidence level, all three specifications are strongly identified, the estimate of γ barely changes when we include time-varying and time invariant observed attributes, and the estimates of γ above 0.9 in the first two specifications indicate a substantial degree of persistence. Thus, as with weight and height z -scores, while persistence from one period to the next in BMI z -scores is high, it is not attributable to or explained by observed characteristics.

While the first two specifications differ little across Tables 5 – 7, the results from the fixed effect specification does. As noted above, time invariant, unobserved factors account for roughly 17% of the total persistence in weight z -scores and 36% for height z -scores. For BMI, the fixed effects now account for nearly 80% of the total persistence. The economically and statistically meaningful drop in the estimate of γ implies a substantially smaller role for state dependence in the persistence of child BMI. Consequently, the long-run impact of early interventions – that do not alter relevant, time invariant, unobserved attributes – on BMI is quite small. For example, a *one-time* intervention that reduces a child’s BMI prior to kindergarten entry by one standard deviation, *ceteris paribus*, is expected to have essentially no impact on BMI in spring eighth grade. A *permanent* intervention that reduces a child’s BMI by 0.10 standard deviations *every period*, will only result in a long-run decrease in the child’s BMI of roughly 0.13 standard deviations.

When we divide the sample into different sub-groups, we find that the results are qualitatively similar across all three specifications, in contrast to the prior results for weight and height. In terms of the first two specifications, there are essentially no differences across the various groups. For the fixed effect specification, the only minor difference of note is for gender. In this case, the fixed effects account for approximately 80% of total persistence for males and roughly 70% for females. For all the remaining divisions of the sample, time invariant factors account for roughly 73 - 78% of total persistence.

Simulations We next turn to the dynamic simulations based on (9) to provide further analysis of the sources of persistence, the role of time-varying and time invariant observed attributes, and differences across demographic groups. As noted earlier, the simulations are based on the estimates of the fixed effects specification given in (8), along with the subsequent estimates of the fixed effects and their decomposition given in (10) and (11). The results are presented in Tables 8 – 10. Table 8 uses weight z -scores, Table 9 uses height z -scores, and Table 10 uses BMI

z -scores. For each outcome, we simulate four sets of probabilities:

1. $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \geq 85^{\text{th}} \text{ percentile})$,
2. $\Pr(y_{iT} \geq 95^{\text{th}} \text{ percentile} \mid y_{i0} \geq 95^{\text{th}} \text{ percentile})$,
3. $\Pr(y_{iT} \geq 50^{\text{th}} \text{ percentile} \mid y_{i0} \geq 50^{\text{th}} \text{ percentile})$, and
4. $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \leq 50^{\text{th}} \text{ percentile})$,

where T denotes spring eighth grade and period 0 corresponds to fall kindergarten. Note, the percentile outcomes are based on the underlying reference population used in the CDC 2000 growth charts, *not* the current sample. Thus, the 85th and 95th percentiles correspond to usual cutoffs for overweight and obese when examining BMI. Finally, each table presents the *benchmark* probability, which is the empirical probability observed in the data (i.e., not estimated), for comparison.

Table 8a displays the results for the $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \geq 85^{\text{th}} \text{ percentile})$ for weight z -scores. For the full sample, the benchmark probability is 0.84. In other words, the probability of being above the 85th percentile in the terminal period conditional on being above the 85th percentile in the initial period is 84%. This is consistent with the high degree of persistence noted previously. Panel I contains the simulated probabilities when time-varying unobservables are ignored (i.e., $\varepsilon_{it} = 0$ for all i, t) and time invariant heterogeneity is altered first by removing it entirely (by setting α at the sample mean of $\hat{\alpha}$) and then by retaining the heterogeneity in α , but breaking its correlation with x and y_0 by giving each child a random draw from the empirical distribution of $\hat{\alpha}$. In the first case, the conditional probability of staying above the 85th percentile falls to about 0.753; it falls to roughly 0.576 in the second case. The fact that the conditional staying probability drops noticeably from the benchmark in the second case, but only marginally in the first case, indicates that it is not the variation in α across children *per se* that determines persistence, but rather the *correlation* between α and the time-varying covariates that explain a little over 30% of total persistence (i.e., $1 - (0.576/0.84)$). Since the prior results in Tables 5 – 7 indicate that the time-varying, observed covariates, x , have little explanatory power, this suggests it is really the correlation between α and the initial condition, y_0 , that explains nearly one-third of the total persistence. In other words, children with high initial conditions – measured by weight z -score upon kindergarten entry – also have high values of α , and this combination is responsible for one-third of the conditional staying probability over the span of kindergarten through eighth grade.

Panels II and III in Table 8a assess whether the importance of α is due to time invariant observed factors, w , or unobserved factors, η . The first simulation in Panel II sets η equal to zero and leaves w at its actual value. The result is very similar to the first case in Panel I, when α is set equal to its sample mean. In this case, the conditional staying probability is 0.727, implying that it is the setting of η to its sample mean that is driving the first result in Panel I. When instead children are given a random draw for w from its empirical distribution, the probability changes only modestly to 0.703. This is consistent with the results in Tables 5 – 7, where we found little explanatory power for the time invariant, observed covariates. In Panel III, however, when children retain their own observed factors, x and w , but receive a random draw for η from its empirical distribution, the conditional staying probability

falls to 0.593. As such, it is the correlation between time invariant, *unobserved* factors and the initial condition, y_0 , that is responsible for roughly one-third of the conditional staying probability.

Lastly, Panels IV, V, and VI report the simulated probabilities obtained when children retain their α , but receive draws of either time-varying, observed, x , or unobserved, ε , attributes or both from their respective empirical distributions. The results indicate no impact from altering either, again consistent with the prior results in Tables 5 – 7. In sum, the simulations for the full sample indicate that about one-third of the conditional staying probability for weight is due to *persistent, unobserved* risk factors such genetic endowments, early life health shocks, time invariant environmental factors, etc. The remainder is due to state dependence. The fact that two-thirds of persistence is due to state dependence is encouraging in that early interventions, to the extent that they are successful in reducing weight prior to kindergarten, can have long-run effects on weight during middle school.

The remainder of Table 8a reports the simulated probabilities for the different sub-groups. In addition to the simulations presented for the full sample, when drawing from empirical distributions, we draw not only from the full sample, but also from within one’s own group and outside one’s own group. This enables us to see the effects of differences in the distributions of the various components of the model across groups.²⁶

In the interest of brevity, we highlight a few salient findings. First, the benchmark probability differs little by gender or urban status. However, non-white children, children with a mother without a four-year college degree, or children residing in a low SES household have a higher benchmark conditional staying probability (race: 0.861 versus 0.823; education: 0.870 versus 0.748; SES: 0.880 versus 0.820). Second, as in the full sample, altering values for the time-varying, observed and/or unobserved factors, x and ε , has little impact on the conditional staying probability for all of the various groups.

Third, altering values for α , or its components, matters across all groups, but in different ways. For non-whites, children with a mother without a four-year college degree, and children residing in a low SES household, replacing α with the (full) sample mean has little effect on the conditional staying probability. This suggests that these groups have such poor initial conditions, y_0 , that even replacing α with the sample mean is not sufficient to move children in these groups who are initially above the 85th percentile below the 85th percentile in the terminal period. Instead, only when α is replaced by a random draw, particularly a random draw from outside one’s own group, does the conditional staying probability drop to 0.50 – 0.60. Fourth, while the distributions of α do not differ by much across the different groups, the distributions of the observed component, w , does. In particular, females, children in urban residences, children with a four-year college educated mother, and children in high SES families possess time invariant, observed factors associated with lower conditional staying probabilities. However, the fact that the overall distribution of α differs little across groups indicates that much of the variation in α is due to the unobserved component, η , which differs little across groups.²⁷ Thus, in the end, the amount of persistence due to the fixed effects as opposed to state dependence is roughly constant across the groups.

Table 8b displays the results for the $\Pr(y_{iT} \geq 95^{\text{th}} \text{ percentile} \mid y_{i0} \geq 95^{\text{th}} \text{ percentile})$ for weight z -scores. Comparing the results in Tables 8a, three primary differences emerge. First, the benchmark probability is lower in the full

²⁶Figures C7-C12 in Appendix C also plot the empirical distributions to facilitate comparisons.

²⁷This is borne out graphically; see Figures C7 – C8 in Appendix C.

sample and for each demographic group (e.g., 0.762 for the full sample). Thus, there is less persistence in extreme upper tail of the weight distribution. Moreover, the difference in the benchmark probability across each demographic group is now economically meaningful (race: 0.732 versus 0.795 favoring whites; gender: 0.710 versus 0.807 favoring females; urban status: 0.749 versus 0.791 favoring non-urban; education: 0.646 versus 0.790 favoring four-year college educated; SES: 0.740 versus 0.799 favoring high SES). Second, the vast majority of the persistence in obesity status is due to time invariant heterogeneity, α ; even more so than in Table 8a. Thus, state dependence, as well as time-varying factors, x and ε , do not play much of a role. For example, replacing α with the sample mean for all children reduces the conditional staying probability in the full sample to less than 15% and less than 20% within each demographic group. Even replacing α with a random draw from its empirical distribution cuts the conditional staying probability by nearly one-half in all cases. Third, unlike in Table 8a, we find that setting η to zero in Panel II results in lower conditional staying probabilities than in Panel III when η is replaced by random draws from different empirical distributions. This indicates that giving children initially above the 95th percentile an average draw from the distribution of η (i.e., setting η to zero) is sufficient to bump most of the children below the 95th percentile by the terminal period, whereas this is not sufficient when using the 85th percentile as the threshold.

Table 8c displays the results for the $\Pr(y_{iT} \geq 50^{\text{th}} \text{ percentile} \mid y_{i0} \geq 50^{\text{th}} \text{ percentile})$ for weight z -scores. In comparison to the results in the previous two tables, two noticeable differences are present. First, the conditional staying probabilities are much higher in the full sample and across the different demographic groups (around 0.9 in all cases). Moreover, there is little difference across the groups; the small differences that do arise favor different groups than in the prior tables. For example, the conditional staying probability is now slightly higher for females than males (0.918 versus 0.894). Second, the simulations cause less sizeable changes in the conditional staying probabilities than in the prior tables. However, in some cases, our simulations actually increase the amount of persistence. For example, replacing α with the sample mean, or setting η to zero, increases the conditional staying probabilities to near unity in all cases. However, replacing η with a random draw from one of the empirical distributions continues to reduce persistence, but only modestly. This suggests that most children above the median in the initial period have unfavorable time invariant, unobserved factors, η ; a small number of children who have favorable draws despite being initially above the median are able to move below the median by the terminal period. If η were randomly assigned, even more children would be able to move below the median by eighth grade.

Finally, Table 8d presents the results for the $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \leq 50^{\text{th}} \text{ percentile})$ for weight z -scores. This case illuminates factors associated with relatively extreme weight gain during early childhood (i.e., sizeable upward mobility as opposed to persistence). In terms of the benchmark case, the probability of moving from below the median at entry into kindergarten to above the 85th percentile by the end of eighth grade is roughly 12% in the full sample. While this probability does not differ a lot across the demographic groups, small differences arise surprisingly favoring non-whites and urban residents, as well as children with a mother with a four-year college degree and those residing in high SES households (race: 0.113 versus 0.121; gender: 0.104 versus 0.132; urban: 0.104 versus 0.124; education: 0.079 versus 0.131; SES: 0.106 versus 0.145).

Turning to the simulations, we obtain a few noteworthy findings. First, time-varying factors, x and ε , continue to not play any meaningful role. Second, replacing α with the sample mean reduces the probability of crossing

the 85th percentile conditional on starting below the median to zero in all cases. Replacing α with a random draw from different empirical distributions roughly doubles the probability of crossing the 85th percentile relative to the benchmark in all cases. Together, these results imply that children initially below the median tend to have favorable values of α . Specifically, α is not randomly distributed in the population, but rather has a positive (partial) correlation with the initial condition, y_0 . Only the few children with extremely unfavorable draws of α experience extreme upward mobility. Moreover, if α were randomly assigned, the probability of moving from below the median to above the 85th percentile would roughly double.

Third, the effect of randomly assigning α is due to randomly assigning the time invariant, unobserved factors, η . Randomly assigning the time invariant, observed factors, w , has little impact on the probability of extreme upward mobility. Moreover, removing time invariant, unobserved factors by setting η to zero reduces the probability of extreme upward mobility to nearly zero in all cases. The implication is that children below the median tend to have favorable draws of α , which really means favorable draws of time invariant, unobserved factors, η .

Tables 9a – 9d present the analogous set of results for height z -scores. While height *per se* is not a policy concern in the United States, it is interesting to compare the dynamics of height with those of weight. In addition, it is useful to examine the individual components of BMI prior to assessing BMI z -scores in Tables 10a – 10d. In terms of the benchmark probabilities, a few differences emerge relative to the previous results for weight. First, the benchmark probabilities are lower for height than the corresponding probabilities for weight in all cases across Tables 9a – 9d. For example, $\Pr(y_{iT} \geq 50^{\text{th}} \text{ percentile} \mid y_{i0} \geq 50^{\text{th}} \text{ percentile})$, $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \geq 85^{\text{th}} \text{ percentile})$, $\Pr(y_{iT} \geq 95^{\text{th}} \text{ percentile} \mid y_{i0} \geq 95^{\text{th}} \text{ percentile})$ are 0.786, 0.606, and 0.467, respectively, in the full sample for height; 0.906, 0.840, and 0.762, respectively, for weight. Thus, persistence in the upper half of the distribution is lower, albeit still high, for height. Second, while there may exist more mobility in terms of height, extreme upward mobility for height is less common than for weight. In the full sample, $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \leq 50^{\text{th}} \text{ percentile})$ is 0.030 for height and 0.118 for weight.

Turning to the simulations, a few patterns emerge. First, while the time-varying factors, x and ε , have a bit more impact on height than weight, their combined effect is still modest. In Tables 9a – 9c, replacing x and/or ε with different values increases the conditional staying probabilities in all cases for the full sample. This indicates that, on average, children initially above the median tend to have less favorable (in terms of raising height) time-varying attributes, partially offsetting the child’s height in the initial period.

Second, as with weight, most of persistence in height is attributable to time invariant factors captured by α . However, the patterns are different. In Tables 9a and 9b, we find that replacing α with the sample mean drops the conditional staying probabilities above the 85th and 95th probabilities to zero for the full sample and all demographic groups. Further analysis reveals that this stems from the unobserved component captured by η ; varying the time invariant, observed component, w , has no impact. This implies that children in the upper tail of the height distribution upon entry to kindergarten possess time invariant, unobserved attributes that tend to keep them in the upper tail. Replacing these attributes with the sample mean, or a random draw, essentially guarantees these children will fall out of the upper tail by the end of eighth grade. Replacing the unobserved component of the fixed effects, η , with a random draw similarly reduces the conditional staying probabilities, but not as much; the probabilities fall to around

0.25 and 0.10 in Tables 9a and 9b, respectively. This is perhaps not surprising as genetics and early biological factors presumably play a large role in determining child height. In Table 9c, we find that replacing α with the sample mean *increases* the conditional staying probabilities above the median to near unity for the full sample and all demographic groups, consonant with weight. However, for height, the time invariant, observed component, w , plays more of a role. In particular, the results indicate that whites, males, non-urban residents, children with four-year college educated mothers, and children in high SES households possess time invariant, observed factors positively associated with being above the median in the height distribution. Thus, whereas time invariant, observed factors play little role in the determination of persistence in the upper tail, they do affect mobility in the middle of the height distribution.²⁸

Finally, Table 9d suggests that extreme upward mobility in height is rare since children initially below the median have unfavorable draws of time invariant, unobserved heterogeneity, η . Replacing η with its sample average would eliminate extreme upward mobility entirely as the few cases of observed extreme upward mobility is due to a handful of children having very favorable values of η despite being below the median upon entry to kindergarten. On the other hand, replacing η with a random draw would increase extreme upward mobility by four- to five-fold.

Next, we turn to Tables 10a – 10d, displaying the results for BMI z-scores. Table 10a continues to explore the conditional probability of remaining above the 85th percentile; Tables 10b and 10c report the conditional staying probabilities using the 95th percentile and median as the threshold. In each table, the benchmark probability lies in between the conditional staying probabilities for weight and height reported in the corresponding Tables 8a – 8c and 9a – 9c. This is also true for most of the demographic sub-groups. Furthermore, the benchmark probabilities are consistent with the high degree of persistence in BMI documented earlier. For example, the conditional probability of staying above the 85th percentile is 0.746 in the full sample (see Table 10a); 0.715 for staying above the 95th percentile (see Table 10b). Lastly, the benchmark probabilities are notable in that the gaps between racial, education, and SES groups in Tables 10a and 10b are larger than the corresponding gaps for either weight or height separately. For instance, the conditional probability of staying above the 95th percentile for BMI is 0.664 for whites and 0.769 for non-whites. The corresponding gap for weight (height) is 0.732 versus 0.795 (0.481 versus 0.446). Thus, demographic differences in persistence of remaining in the upper tail of the BMI distribution are sizeable.

When we turn to the simulated probabilities, a few findings stand out. First, altering the values of the time invariant components in Panels I, II, and III of Tables 10a – 10c yields results that are qualitatively similar to those reported in Tables 9a – 9c for height. In particular, in Panel I we find that replacing α with the sample mean reduces the conditional probability of staying above the 85th and 95th percentiles to zero in nearly every case (see Tables 10a and 10b), and to unity in every case when we use the median as the threshold (see Table 10c). Moreover, this is predominantly due to the salient role of time invariant, *unobserved* factors, η . Variation in time invariant, observed factors, w , explain a modest amount of variation in the conditional probability of staying above the 85th percentile (see Table 10a), but not when using the 95th percentile or median as the threshold (see Tables 10b and 10c). Thus, the results are consistent with children in the upper part of the BMI distribution possessing less favorable time invariant factors, particularly those unobserved. Moreover, the only children able to move below the median

²⁸Estimates of (11) indicate that such observable factors include higher birthweight, residing in the midwest or west, and having a mother with a later age at first birth.

conditional on being above the median at kindergarten entry are those with extremely favorable draws of η despite their unfavorable initial condition.

Second, in Panel II of Table 10a, where variation in time invariant, observed factors, w , plays a modest role, we find that whites, females, non-urban residents, children with a mother with a four-year college degree, and children in high SES households continue to possess more favorable attributes. The largest discrepancy occurs along racial lines. If we set η to zero and give white children a random draw of w from the empirical distribution for whites (non-whites), we obtain a conditional staying probability of 0.015 (0.121). Setting η to zero and giving non-white children a random draw of w from the empirical distribution for whites (non-whites), we obtain a conditional staying probability of 0.015 (0.118). Thus, the variation in the distribution of time invariant, observed factors is responsible for roughly a ten percentage point difference along racial lines in the conditional probability of remaining above the 85th percentile, *ceteris paribus*. Finally, as in all the analysis of weight and height, we find very little role for variation in time-varying factors, either observed or unobserved.

The last table, Table 10d, presents the results for the $\Pr(y_{iT} \geq 85^{\text{th}} \text{ percentile} \mid y_{i0} \leq 50^{\text{th}} \text{ percentile})$ for BMI z-scores. In terms of the benchmark case, the probability of moving from below the median at entry into kindergarten to above the 85th percentile by the end of eighth grade is 0.142 in the full sample. Sizeable differences arise across some of the demographic groups; the conditional probability is about twice as large for children with a mother without a four-year college degree and about seven percentage points higher for children residing in a low SES household (education: 0.087 versus 0.162; SES: 0.121 versus 0.192).

Turning to the simulations, we obtain a few findings. First, time-varying factors, x and ε , continue to not play any meaningful role. Second, replacing α with the sample mean reduces the probability of crossing the 85th percentile conditional on starting below the median to zero in all cases, just as in Tables 8d and 9d. Replacing α with a random draw from different empirical distributions roughly increases the probability of crossing the 85th percentile by two- to three-fold relative to the benchmark in all cases. Together, these results continue to imply that children initially below the median tend to have favorable values of α . Only a few children with extremely unfavorable draws of α , despite being initially below the median, experience extreme upward mobility. Moreover, if α were randomly assigned, the probability of moving from below the median to above the 85th percentile would increase substantially.

Third, the effect of altering α is due to altering the time invariant, unobserved factors, η . However, as in Table 10a, the time invariant, observed factors, w , explain a modest amount of the variation in the probability of extreme upward mobility overall, as well as across racial, education, and SES groups. Specifically, whereas removing time invariant, unobserved factors by setting η to zero reduces the probability of extreme upward mobility to nearly zero for weight and height, this is not the case for BMI as the probability varies from roughly 1 - 8%.

Discussion While there are many subtle results emerging from the dynamic regression analysis, perhaps the most important is that persistence in weight, height, and BMI is quite high over the period spanning kindergarten through eighth grade and that this persistence – particularly persistence in the upper tails of the distributions – is predominantly driven by *persistent, unobserved* heterogeneity. Time-varying observed and unobserved factors play little role. Time invariant, *observed* heterogeneity plays a modest role in some instances. In particular, children

who are male or black, rural or northeast residents, non-native English speakers, had a high birthweight, and have a mother with low education, a low age at first birth, or who participated in the labor force during the child’s infancy tend to have higher BMI. State dependence – persistence due to a causal effect of past outcomes on current outcomes – plays a prominent role for weight only.

That said, it is worth re-iterating that the majority of persistence in the upper tails of the distributions of weight, height, and BMI is due to time invariant, unobserved factors. This is also borne out through examination of Figures C7 – C12 in Appendix C. For example, Figures C11 and C12 present the decompositions for BMI z -scores by demographic group. Focusing on the top row of Figure C11, we see that the distribution of BMI z -scores for non-whites is slightly shifted to the right relative to the distribution for whites. More important to note is that the distributions range from roughly -3 to 3 (i.e., the scaling on the x -axis). The next two graphs plot the distributions of $x\hat{\beta}$ and $\hat{\alpha}$ by race. Here, we see the distributions of $x\hat{\beta}$ ranges from about -0.2 to 0.1, whereas the distributions of $\hat{\alpha}$ range from roughly -2 to 2. The top row of Figure C12 decomposes the distributions of $\hat{\alpha}$ into the observed portion, $w\hat{\delta}$, and the unobserved portion, $\hat{\eta}$. Here, we find that while the distributions of $\hat{\alpha}$ range from about -2 to 2, the distributions of the observed (unobserved) components range from roughly 0 to 1 (-2 to 2).

In sum, then, the simulations and figures yield a coherent picture whereby the majority of the variation in weight, height, and BMI is due to heterogeneity, particularly unobserved heterogeneity, that does not vary during primary school. The implication is that, while earlier intervention is preferred to later interventions, *only* interventions that alter the crucial, time invariant, unobserved risk factors captured by η are likely to be effective in the long-run. Interventions that leave the attributes captured by η unaltered are likely to have, at best, minimal short-run effects and little to no long-run effects. This is entirely consistent with the findings reported in Davis and Gebremariam (2010). There, the authors document that community-based interventions designed to combat childhood obesity that were deemed as successful according to the analysis of data collected via randomized control trials did not produce lasting effects. Eventually, children returned to their “natural state” (p. 22).

This naturally begs the question concerning the attributes reflected by η . From the analysis presented here, all we can conclude is that they are unobserved in our set of covariates taken from the ECLS-K and they do not vary during the primary school years. The prior literature, discussed earlier, posits some possibilities: prenatal attributes such as maternal BMI, maternal weight gain, maternal smoking, and gestational diabetes requiring insulin and post-natal attributes such as breastfeeding, transitions to solid foods, and age at adiposity rebound. While we do control for birthweight, birthweight alone is not a sufficient proxy for these early influences on fetal development as noted earlier. Finally, while time invariant, environmental factors, such as neighborhood characteristics, are also captured by η , prior evidence suggests that these are not likely to play a significant role. For example, prior studies using twins that are reared apart conclude that familial environment does not play a salient role (Eriksson et al. 2001). In an attempt to delve into this issue, we undertake one final analysis using the ECLS-B. We turn to it now.

ECLS-B In our final analysis, we utilize data from the restricted version of the ECLS-B. Collected by the US Department of Education, the ECLS-B collects information on a nationally representative cohort of children born in 2001 at 9 months of age, two years, four years, and five years. As with the ECLS-K, our final sample consists of a

balanced sample of children for whom we have valid measures of age, gender, height, and weight.²⁹ Given the age of the sample, we convert weight into z -scores; height is measured in centimeters.

The following time invariant covariates are included: gender, race (white, black, Hispanic, Asian, and other), mother’s age at first birth, birthweight indicators (normal or low), indicator for intrauterine growth retardation (less than 10%, 10-24%, 25-49%, 50-75%, 76-89%, and 90% and above)³⁰, indicator for premature birth, indicator for birth status (singleton, twin, or higher order birth), mother’s height, mother’s weight prior to pregnancy, mother’s weight gain during pregnancy, indicator for prenatal care (inadequate, intermediate, adequate, or adequate plus), indicator for maternal prenatal vitamin consumption within the three months preceding conception, indicator for maternal prenatal vitamin consumption during the first trimester, indicator for maternal smoking within the three months preceding conception, indicator for maternal smoking within the third trimester, indicator if mother has smoked more than 100 cigarettes in her lifetime, indicator for maternal alcohol consumption within the three months preceding conception, number of current smokers in the household, region (northeast, midwest, south, and west), city type (urban, suburban, or rural), indicator for mother’s participation in WIC (Women’s, Infants, and Children) during pregnancy, indicator for mother’s participation in WIC during infancy, and scores on infant mental and motor assessments administered at 9 months.

The following time-varying covariates are included: age, mother’s education (less than high school, high school/GED, some college, four-year college degree, and more than four years of college), an index of SES status, indicator for the household being in poverty, number of children’s books in the household, household size, family type (two parents plus siblings, two parents and no siblings, one parent and siblings, one parent and no siblings, and other), indicator for biological mother present, indicator for biological father present, indicator for no father present, indicator for no mother present, indicator for parental respondent’s marital status, indicator of current TANF participation, indicator of current FSP participation, indicator for health insurance, indicator for current medicaid participation, indicator for current WIC participation, indicator for household food security (household never worried about running out of food), hours per day spent watching television during the school week, indicator for household rules regarding television watching, neighborhood safety (very safe, somewhat safe, and not safe), mother’s labor force status (full-time, part-time, and not working), indicators for primary child care arrangement (parents, other relatives, non-relatives, center-based care, or Head Start), indicator for school enrollment, indicator if English is the primary home language, and mother’s weight. For all covariates (except gender, age, height, and weight), we include dummy variables for missing observations.

The results are presented in Tables 11-14. Tables 11-12 display the model estimates; Tables 13-14 present the simulation results. Figures C13-C16 in Appendix C contain the relevant figures.

In terms of the coefficient estimates, the results in Table 11 using weight z -scores are fairly similar to those obtained using the ECLS-K when omitting child-specific fixed effects. Specifically, the estimates of γ in the full sample and each of the demographic sub-groups is statistically significant and ranges from 0.84 to 0.89. As with the

²⁹The possible sample size is roughly 6,950; the initial sample size in the first wave is about 10,700. Restricting the sample to those with valid data on age, gender, height, and weight reduces the sample size to approximately 5,450. This is the final sample size per wave in the regression analysis. Note, all sample sizes are rounded to the nearest 50 per NCES restricted data regulations for the ECLS-B.

³⁰Intrauterine growth retardation measures the ratio of birthweight to predicted weight based on gestation age.

ECLS-K, the fact that the estimate of γ does not change moving from (6) to (7) implies that our lengthy vector of time-varying and time invariant observed factors explain none of the persistence in weight status for infants and young children. Given the additional time invariant controls available in the ECLS-B, this is striking. Moreover, the estimates of γ near 0.9 indicate a substantial degree of persistence. However, unlike in the ECLS-K, inclusion of child-level fixed effects explains the majority of this persistence. Here, the estimate of γ falls to 0.124 (standard error of 0.013) in the full sample; the estimates vary from 0.105 to 0.144 across the various sub-groups. This implies that time invariant, *unobserved* factors explain about 85% of the observed persistence in weight z -scores during early childhood. In contrast, only 17% of observed persistence in weight z -scores during primary school is due to time invariant, unobserved heterogeneity. Again, given that we observe many more time invariant attributes of children in the ECLS-B, this is a startling result.

Table 12 displays the corresponding results for height. Four interesting patterns emerge. First, persistence in height in the models not controlling for any other covariates – based on the specification in (6) – is of a much smaller magnitude than found in the ECLS-K when assessing height for older children or in the ECLS-B when assessing weight. Second, when controlling for observed heterogeneity – based on the specification in (7) – persistence actually increases by about 15%. This is consistent with a negative correlation between the initial condition for height, y_0 , which is really ‘length’ at nine months of age, and observed heterogeneity associated with greater height. Third, as with weight in the ECLS-B, there is very little difference across the demographic sub-groups. Finally, when child-level fixed effects are included, the estimates of γ become *negative* and statistically significant (although always below 0.06 in absolute value). Thus, *all* of the persistence in child height up to age five is attributable to *time invariant, unobserved* heterogeneity.

Tables 13-14 report the results of the same simulations performed in Tables 8-10 for the ECLS-K. In the interest of brevity, we only briefly summarize the results. First, the benchmark probabilities for both weight and height, along with the distributions of observed and unobserved, time-varying attributes, do not differ across the demographic sub-groups. As such, not only do the benchmark probabilities not vary across groups, but replacing a child’s own x and/or ε with draws from the opposite group has no effect on persistence. Second, time-varying attributes, both observed and unobserved have no effect on persistence. Given the lengthy vector of attributes, as well as the plethora of time-varying, unobserved attributes captured by ε , this continues to be a noteworthy finding.

Third, as in the ECLS-K, time invariant heterogeneity continues to play a prominent role in understanding persistence in child weight and height. For weight, replacing α with its sample mean explains virtually all persistence through age five. Moreover, replacing the fixed effect of a child initially below the median with the sample mean roughly doubles the probability that the child’s weight will exceed the 85th percentile at age five. For height, replacing α with its sample mean explains most, but not all, persistence. However, replacing the fixed effect of a child initially below the median with the sample mean does not alter the probability that the child’s height will exceed the 85th percentile at age five.

Fourth, time invariant, *observed* attributes play a more prominent role, particularly for height, in explaining persistence up to age five than in the ECLS-K analysis of primary school children. This could be attributable to two sources. On the one hand, the time invariant, observed attributes may play a more important role in the

determination of child weight and height prior to age five. On the other hand, the vector of controls is not identical across the two data sources. Examining the results of (11), the most important covariates relate to birthweight, birth status (i.e., singleton, twin, or higher order birth), intrauterine growth retardation, breastfeeding duration, mother’s height, and mother’s weight gain during pregnancy. That said, as measured by the R^2 , 19% (22%) of the variation is α is explained by the covariates included in (11) when examining weight (height).

Finally, time invariant attributes, both observed and unobserved, differ across the various demographic sub-groups, particularly along racial lines. For example, in Table 13a, the probability of a white (non-white) child’s weight persisting above the 85th percentile when the child’s own fixed effect, α , is replaced by a random draw from the sample distribution is 0.284 (0.242). Replacing the child’s own fixed effect, α , with a random draw from the sample distribution for the child’s own racial group, the probability of persisting above the 85th percentile is 0.216 (0.284). Replacing the child’s own fixed effect, α , with a random draw from the sample distribution from the opposite racial group, the probability of persisting above the 85th percentile is 0.333 (0.179). Similar patterns hold in the other panels for weight and height.

In sum, the results from the sample of children aged five and younger in the ECLS-B are consistent with the sample of primary school children in the ECLS-K. Namely, persistence in weight and height is quite high, and this persistence is mainly driven by *time invariant* heterogeneity. However, in contrast to the primary school sample, time invariant, *observed* attributes play a bit more of an important role. In particular, while the associations between birthweight, gestation age, maternal height and weight, and single versus multiple birth and fetal development are not strong, perhaps due to the complexities involved these relationships that are only currently beginning to be understood in the medical literature, these controls do play a small role in explaining persistence. Nonetheless, the primary determinants of fetal and infant development that may be critical in placing children on an “obesity trajectory” remain unobserved, even in the ECLS-B. Such unobserved attributes are likely to include maternal BMI (as opposed to weight), gestational diabetes treated with insulin, periods of undernutrition during pregnancy, and the timing of transitions to solid foods.

6 Conclusion

Concern over childhood obesity has risen dramatically over the past decade. However, our knowledge has not kept pace with this concern. In particular, our knowledge over how weight evolves over the life cycle, from *in utero* to adulthood, is sorely lacking. Existing evidence documents strong correlations between adolescent health status and adult health status. Unfortunately, whether this correlation reflects state dependence, observed heterogeneity, or unobserved heterogeneity is unknown. Moreover, when this persistence in weight status begins – adolescence, early childhood, postnatally, or prenatally – is also unknown. Prior work has identified three ‘critical’ development periods as it relates to obesity: *in utero*, adiposity rebound (around age four to six), and adolescence. However, as Dietz (1997, p. 1886S) notes, “The relative contribution of each of these critical periods to the prevalence, morbidity and mortality of adult obesity remains uncertain.”

Better understanding of the dynamics of weight is crucial for sound policymaking. If weight status is highly

persistent and the source of this persistence is state dependence, then small (permanent) changes will have large, long-run effects even if the contemporaneous effects are small. However, if persistence is due to biological or environmental factors that are time invariant, then the *only* changes that will have long-run effects are those that alter these underlying factors. Absent such effects, interventions will not alter the long-run weight status of individuals even if they have contemporaneous effects.

The evidence presented here indicates, first, that there is significant persistence in weight and height starting during infancy and BMI starting in kindergarten and, second, that this persistence is predominantly due to time invariant heterogeneity across individuals determined at birth or shortly thereafter, not state dependence. Moreover, little variation in these time invariant attributes across individuals is explained by attributes observed in the data analyzed here. The few time invariant, observed attributes that do seem to play a role in the persistence of weight over the early part of the life cycle relate to fetal and infant nutrition. This suggests that of the three ‘critical’ periods noted in Dietz (1997), *in utero* (and post-natal) plays the largest role. It also implies that strategies to reverse the current childhood obesity epidemic may need to start even earlier than previously thought, namely *in utero*. This confirms recent policy prescriptions advocated elsewhere. For example, Brisbois et al. (2012, p. 347) concludes: “Given that obesity may be programmed *in utero* and during early infancy, preventive measures should be initiated preconception, during pregnancy and continue throughout early childhood.” Examples may include altering institutional rules concerning federal nutrition programs, such as SNAP or WIC, or education provided under these programs, as they relate to pregnant women (e.g., Baum 2012).

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Table 1a. Transition Matrices: Percentile Weight**I. Full Sample**

	Q1	Q2	Q3	Q4	Q5
Q1	0.533	0.245	0.133	0.060	0.029
Q2	0.291	0.316	0.205	0.132	0.056
Q3	0.125	0.258	0.303	0.207	0.107
Q4	0.047	0.149	0.268	0.336	0.200
Q5	0.004	0.030	0.091	0.266	0.610

II. White

	Q1	Q2	Q3	Q4	Q5
Q1	0.517	0.238	0.141	0.068	0.037
Q2	0.290	0.306	0.197	0.141	0.066
Q3	0.130	0.262	0.301	0.194	0.113
Q4	0.056	0.168	0.264	0.321	0.191
Q5	0.007	0.025	0.097	0.277	0.594

III. Non-White

	Q1	Q2	Q3	Q4	Q5	
Q1	0.560	0.258	0.117	0.048	0.018	$\chi^2=37.82$ p=0.00
Q2	0.291	0.328	0.211	0.118	0.052	
Q3	0.107	0.248	0.330	0.218	0.097	
Q4	0.038	0.143	0.273	0.337	0.209	
Q5	0.003	0.023	0.069	0.281	0.623	

IV. Male

	Q1	Q2	Q3	Q4	Q5
Q1	0.505	0.257	0.149	0.058	0.032
Q2	0.290	0.293	0.211	0.145	0.060
Q3	0.144	0.253	0.288	0.207	0.108
Q4	0.054	0.174	0.263	0.320	0.189
Q5	0.006	0.026	0.088	0.270	0.611

V. Female

	Q1	Q2	Q3	Q4	Q5	
Q1	0.565	0.236	0.121	0.055	0.023	$\chi^2=33.40$ p=0.03
Q2	0.289	0.328	0.200	0.120	0.063	
Q3	0.111	0.265	0.305	0.205	0.114	
Q4	0.032	0.147	0.274	0.352	0.195	
Q5	0.001	0.026	0.097	0.270	0.606	

VI. Urban

	Q1	Q2	Q3	Q4	Q5
Q1	0.545	0.259	0.121	0.056	0.020
Q2	0.303	0.303	0.208	0.117	0.069
Q3	0.111	0.257	0.310	0.224	0.099
Q4	0.041	0.144	0.267	0.353	0.195
Q5	0.003	0.035	0.094	0.251	0.617

VII. Non-Urban

	Q1	Q2	Q3	Q4	Q5	
Q1	0.526	0.239	0.138	0.064	0.034	$\chi^2=16.91$ p=0.66
Q2	0.289	0.324	0.197	0.139	0.051	
Q3	0.130	0.260	0.303	0.199	0.107	
Q4	0.051	0.152	0.270	0.323	0.204	
Q5	0.004	0.028	0.088	0.276	0.604	

VIII. Less Than College

	Q1	Q2	Q3	Q4	Q5
Q1	0.540	0.235	0.140	0.057	0.028
Q2	0.295	0.323	0.194	0.138	0.050
Q3	0.121	0.261	0.301	0.205	0.113
Q4	0.042	0.157	0.286	0.320	0.195
Q5	0.001	0.024	0.080	0.281	0.615

IX. College

	Q1	Q2	Q3	Q4	Q5	
Q1	0.522	0.285	0.107	0.067	0.019	$\chi^2=39.97$ p=0.01
Q2	0.284	0.297	0.239	0.127	0.054	
Q3	0.137	0.227	0.326	0.206	0.105	
Q4	0.045	0.162	0.241	0.328	0.224	
Q5	0.013	0.028	0.088	0.273	0.598	

X. Low SES

	Q1	Q2	Q3	Q4	Q5
Q1	0.575	0.215	0.131	0.052	0.026
Q2	0.266	0.341	0.220	0.126	0.047
Q3	0.115	0.266	0.281	0.228	0.109
Q4	0.041	0.156	0.294	0.315	0.194
Q5	0.002	0.021	0.075	0.279	0.623

XI. High SES

	Q1	Q2	Q3	Q4	Q5	
Q1	0.521	0.266	0.124	0.059	0.030	$\chi^2=33.64$ p=0.03
Q2	0.300	0.313	0.195	0.129	0.063	
Q3	0.125	0.246	0.325	0.206	0.099	
Q4	0.046	0.152	0.260	0.333	0.209	
Q5	0.008	0.023	0.097	0.273	0.600	

Notes: Transition probabilities over the period Fall Kindergarten (vertical axis) → Spring 8th Grade (horizontal axis). N = 8370 (full sample), 5330 (white sample), 3040 (non-white sample), 4230 (male sample), 4140 (female sample), 3030 (urban sample), and 5340 (non-urban sample) with sample sizes rounded to the nearest 10 per NCES restricted data regulations. χ^2 test is a test of equality of transition matrices in left and right panels; statistic is distributed with $5 \times (5-1) = 20$ degrees of freedom.

Table 1b. Transition Matrices: Percentile Height

I. Full Sample

	Q1	Q2	Q3	Q4	Q5
Q1	0.609	0.241	0.109	0.031	0.010
Q2	0.235	0.343	0.257	0.127	0.038
Q3	0.100	0.253	0.307	0.246	0.094
Q4	0.038	0.123	0.230	0.343	0.266
Q5	0.018	0.040	0.097	0.255	0.591

II. White

	Q1	Q2	Q3	Q4	Q5
Q1	0.606	0.249	0.105	0.028	0.012
Q2	0.245	0.336	0.267	0.110	0.042
Q3	0.091	0.266	0.311	0.245	0.088
Q4	0.039	0.108	0.227	0.352	0.274
Q5	0.021	0.041	0.097	0.259	0.582

III. Non-White

	Q1	Q2	Q3	Q4	Q5
Q1	0.616	0.241	0.095	0.041	0.007
Q2	0.221	0.349	0.264	0.128	0.038
Q3	0.115	0.227	0.297	0.259	0.102
Q4	0.031	0.148	0.237	0.325	0.259
Q5	0.016	0.035	0.109	0.247	0.594

$\chi^2=24.82$
p=0.21

IV. Male

	Q1	Q2	Q3	Q4	Q5
Q1	0.592	0.259	0.117	0.027	0.005
Q2	0.255	0.330	0.255	0.123	0.037
Q3	0.102	0.231	0.323	0.258	0.087
Q4	0.031	0.136	0.200	0.357	0.277
Q5	0.019	0.042	0.103	0.243	0.594

V. Female

	Q1	Q2	Q3	Q4	Q5
Q1	0.615	0.252	0.092	0.027	0.015
Q2	0.230	0.360	0.248	0.123	0.040
Q3	0.100	0.259	0.308	0.239	0.094
Q4	0.036	0.114	0.238	0.352	0.260
Q5	0.019	0.036	0.099	0.254	0.592

$\chi^2=26.50$
p=0.15

VI. Urban

	Q1	Q2	Q3	Q4	Q5
Q1	0.591	0.257	0.099	0.041	0.012
Q2	0.223	0.338	0.264	0.145	0.030
Q3	0.124	0.235	0.303	0.250	0.089
Q4	0.043	0.134	0.236	0.317	0.271
Q5	0.022	0.036	0.104	0.240	0.598

VII. Non-Urban

	Q1	Q2	Q3	Q4	Q5
Q1	0.620	0.235	0.105	0.031	0.009
Q2	0.243	0.345	0.259	0.111	0.041
Q3	0.088	0.260	0.310	0.250	0.092
Q4	0.034	0.121	0.225	0.352	0.269
Q5	0.016	0.040	0.100	0.256	0.588

$\chi^2=21.60$
p=0.36

VIII. Less Than College

	Q1	Q2	Q3	Q4	Q5
Q1	0.613	0.240	0.098	0.038	0.012
Q2	0.237	0.348	0.256	0.125	0.035
Q3	0.100	0.253	0.303	0.242	0.102
Q4	0.030	0.130	0.230	0.339	0.271
Q5	0.018	0.035	0.109	0.257	0.581

IX. College

	Q1	Q2	Q3	Q4	Q5
Q1	0.568	0.276	0.120	0.026	0.011
Q2	0.255	0.320	0.255	0.134	0.037
Q3	0.111	0.240	0.298	0.276	0.075
Q4	0.045	0.135	0.225	0.332	0.263
Q5	0.020	0.033	0.100	0.232	0.617

$\chi^2=25.16$
p=0.20

X. Low SES

	Q1	Q2	Q3	Q4	Q5
Q1	0.612	0.242	0.099	0.041	0.006
Q2	0.234	0.354	0.247	0.122	0.043
Q3	0.098	0.241	0.326	0.241	0.094
Q4	0.036	0.122	0.201	0.355	0.286
Q5	0.023	0.040	0.128	0.238	0.572

XI. High SES

	Q1	Q2	Q3	Q4	Q5
Q1	0.604	0.245	0.109	0.030	0.013
Q2	0.245	0.337	0.262	0.117	0.039
Q3	0.098	0.249	0.308	0.255	0.090
Q4	0.038	0.131	0.229	0.341	0.260
Q5	0.017	0.037	0.092	0.256	0.599

$\chi^2=19.65$
p=0.48

Notes: See Table 1a for further details.

Table 1c. Transition Matrices: Percentile BMI

I. Full Sample

	Q1	Q2	Q3	Q4	Q5
Q1	0.453	0.254	0.145	0.096	0.053
Q2	0.315	0.269	0.217	0.139	0.060
Q3	0.149	0.265	0.277	0.205	0.105
Q4	0.068	0.174	0.263	0.304	0.191
Q5	0.016	0.037	0.099	0.257	0.591

II. White

	Q1	Q2	Q3	Q4	Q5
Q1	0.438	0.245	0.157	0.105	0.055
Q2	0.322	0.267	0.201	0.141	0.069
Q3	0.160	0.265	0.273	0.191	0.112
Q4	0.065	0.178	0.257	0.294	0.206
Q5	0.016	0.045	0.112	0.270	0.557

III. Non-White

	Q1	Q2	Q3	Q4	Q5
Q1	0.476	0.258	0.118	0.095	0.053
Q2	0.296	0.304	0.227	0.130	0.044
Q3	0.138	0.264	0.299	0.192	0.107
Q4	0.076	0.146	0.270	0.321	0.188
Q5	0.015	0.028	0.086	0.263	0.609

$\chi^2=36.62$
p=0.01

IV. Male

	Q1	Q2	Q3	Q4	Q5
Q1	0.443	0.235	0.161	0.102	0.060
Q2	0.327	0.286	0.183	0.147	0.057
Q3	0.153	0.265	0.271	0.207	0.105
Q4	0.060	0.175	0.284	0.284	0.197
Q5	0.018	0.039	0.102	0.261	0.580

V. Female

	Q1	Q2	Q3	Q4	Q5
Q1	0.469	0.265	0.133	0.087	0.047
Q2	0.301	0.266	0.242	0.139	0.053
Q3	0.143	0.265	0.280	0.202	0.111
Q4	0.076	0.172	0.251	0.297	0.204
Q5	0.012	0.034	0.094	0.275	0.585

$\chi^2=26.09$
p=0.16

VI. Urban

	Q1	Q2	Q3	Q4	Q5
Q1	0.459	0.271	0.132	0.079	0.059
Q2	0.314	0.281	0.223	0.137	0.046
Q3	0.146	0.238	0.274	0.212	0.131
Q4	0.073	0.177	0.271	0.312	0.168
Q5	0.010	0.035	0.099	0.261	0.595

VII. Non-Urban

	Q1	Q2	Q3	Q4	Q5
Q1	0.452	0.242	0.153	0.103	0.050
Q2	0.311	0.268	0.219	0.137	0.066
Q3	0.153	0.273	0.281	0.204	0.090
Q4	0.066	0.179	0.249	0.294	0.213
Q5	0.020	0.038	0.097	0.263	0.582

$\chi^2=26.27$
p=0.16

VIII. Less Than College

	Q1	Q2	Q3	Q4	Q5
Q1	0.455	0.256	0.137	0.096	0.056
Q2	0.314	0.280	0.218	0.137	0.051
Q3	0.151	0.268	0.271	0.199	0.111
Q4	0.068	0.163	0.280	0.312	0.178
Q5	0.012	0.034	0.094	0.257	0.604

IX. College

	Q1	Q2	Q3	Q4	Q5
Q1	0.438	0.264	0.146	0.118	0.034
Q2	0.308	0.250	0.211	0.153	0.080
Q3	0.159	0.273	0.275	0.189	0.105
Q4	0.071	0.172	0.258	0.284	0.215
Q5	0.026	0.041	0.112	0.258	0.563

$\chi^2=27.45$
p=0.12

X. Low SES

	Q1	Q2	Q3	Q4	Q5
Q1	0.472	0.241	0.139	0.100	0.049
Q2	0.298	0.305	0.213	0.141	0.043
Q3	0.156	0.233	0.284	0.214	0.113
Q4	0.070	0.183	0.277	0.275	0.196
Q5	0.006	0.038	0.089	0.269	0.599

XI. High SES

	Q1	Q2	Q3	Q4	Q5
Q1	0.455	0.245	0.153	0.093	0.054
Q2	0.312	0.270	0.201	0.144	0.073
Q3	0.146	0.273	0.287	0.198	0.096
Q4	0.070	0.167	0.261	0.303	0.200
Q5	0.018	0.045	0.098	0.263	0.577

$\chi^2=28.78$
p=0.09

Notes: See Table 1a for further details.

Table 2a. Mobility Measures: Percentile Weight

	Bart	Spear	S-Theil	O-M(0)	R-M(0)		Bart	Spear	S-Theil	O-M(0)	R-M(0)
I. Full Sample											
[1,7]	0.192 (0.002)	0.321 (0.007)	0.271 (0.005)	0.146 (0.005)	0.175 (0.005)						
[1,4]	0.102 (0.002)	0.111 (0.003)	0.134 (0.005)	0.056 (0.003)	0.063 (0.002)						
[4,5]	0.097 (0.001)	0.093 (0.003)	0.108 (0.006)	0.040 (0.002)	0.051 (0.002)						
[5,6]	0.080 (0.001)	0.060 (0.002)	0.072 (0.003)	0.024 (0.001)	0.032 (0.001)						
[6,7]	0.110 (0.001)	0.106 (0.003)	0.149 (0.004)	0.041 (0.001)	0.054 (0.001)						
II. White						III. Non-White					
[1,7]	0.201 (0.003)	0.347 (0.009)	0.273 (0.006)	0.154 (0.007)	0.189 (0.006)	[1,7]	0.180 (0.003)	0.280 (0.010)	0.266 (0.008)	0.133 (0.007)	0.152 (0.006)
[1,4]	0.106 (0.002)	0.118 (0.004)	0.134 (0.005)	0.059 (0.003)	0.067 (0.003)	[1,4]	0.096 (0.002)	0.100 (0.005)	0.134 (0.008)	0.053 (0.004)	0.057 (0.004)
[4,5]	0.101 (0.002)	0.103 (0.003)	0.107 (0.007)	0.040 (0.002)	0.054 (0.002)	[4,5]	0.090 (0.002)	0.078 (0.004)	0.109 (0.012)	0.041 (0.005)	0.044 (0.003)
[5,6]	0.083 (0.001)	0.064 (0.002)	0.070 (0.003)	0.023 (0.001)	0.032 (0.001)	[5,6]	0.076 (0.002)	0.054 (0.003)	0.076 (0.006)	0.025 (0.003)	0.030 (0.003)
[6,7]	0.114 (0.002)	0.115 (0.004)	0.157 (0.005)	0.045 (0.002)	0.058 (0.002)	[6,7]	0.102 (0.002)	0.091 (0.004)	0.136 (0.007)	0.035 (0.002)	0.045 (0.002)
IV. Male						V. Female					
[1,7]	0.199 (0.003)	0.339 (0.010)	0.284 (0.008)	0.156 (0.007)	0.184 (0.006)	[1,7]	0.184 (0.003)	0.298 (0.010)	0.257 (0.007)	0.135 (0.007)	0.164 (0.006)
[1,4]	0.105 (0.002)	0.119 (0.005)	0.144 (0.007)	0.060 (0.004)	0.067 (0.003)	[1,4]	0.098 (0.002)	0.103 (0.004)	0.124 (0.006)	0.052 (0.003)	0.059 (0.003)
[4,5]	0.100 (0.002)	0.100 (0.004)	0.121 (0.010)	0.043 (0.004)	0.054 (0.003)	[4,5]	0.095 (0.002)	0.086 (0.004)	0.096 (0.008)	0.038 (0.003)	0.046 (0.003)
[5,6]	0.078 (0.002)	0.059 (0.003)	0.071 (0.003)	0.020 (0.001)	0.031 (0.001)	[5,6]	0.081 (0.002)	0.061 (0.002)	0.074 (0.004)	0.027 (0.002)	0.033 (0.002)
[6,7]	0.106 (0.002)	0.100 (0.003)	0.149 (0.005)	0.038 (0.002)	0.051 (0.002)	[6,7]	0.112 (0.002)	0.110 (0.004)	0.148 (0.006)	0.045 (0.002)	0.054 (0.002)

Notes: Left column denotes the time span over which mobility is computed. Column headings denote the measure of mobility; see text for definitions. Period 1 = fall kindergarten; Period 4 = spring 1st grade; Period 5 = spring 3rd grade; Period 6 = spring 5th grade; and, Period 7 = spring 8th grade. Bootstrap standard errors based on 250 repetitions (clustered at the child-level) in parentheses. N = 8370 (full sample), 5330 (white sample), 3040 (non-white sample), 4230 (male sample), 4140 (female sample), 3030 (urban sample), and 5340 (non-urban sample) with sample sizes rounded to the nearest 10 per NCES restricted data regulations. See text for definition of mobility measures.

Table 2a (cont.). Mobility Measures: Percentile Weight

	Bart	Spear	S-Theil	O-M(0)	R-M(0)		Bart	Spear	S-Theil	O-M(0)	R-M(0)
VI. Urban						VII. Non-Urban					
[1,7]	0.188 (0.004)	0.307 (0.011)	0.268 (0.009)	0.133 (0.007)	0.165 (0.007)	[1,7]	0.195 (0.003)	0.328 (0.009)	0.273 (0.006)	0.153 (0.006)	0.180 (0.005)
[1,4]	0.100 (0.002)	0.107 (0.005)	0.125 (0.008)	0.051 (0.004)	0.060 (0.004)	[1,4]	0.103 (0.002)	0.113 (0.004)	0.140 (0.006)	0.059 (0.003)	0.065 (0.003)
[4,5]	0.095 (0.002)	0.092 (0.005)	0.100 (0.010)	0.041 (0.005)	0.049 (0.003)	[4,5]	0.098 (0.002)	0.094 (0.004)	0.113 (0.007)	0.040 (0.002)	0.051 (0.002)
[5,6]	0.078 (0.002)	0.058 (0.003)	0.075 (0.005)	0.026 (0.002)	0.032 (0.003)	[5,6]	0.082 (0.001)	0.062 (0.002)	0.071 (0.003)	0.023 (0.001)	0.032 (0.001)
[6,7]	0.109 (0.002)	0.102 (0.004)	0.152 (0.007)	0.042 (0.002)	0.052 (0.002)	[6,7]	0.110 (0.002)	0.108 (0.003)	0.148 (0.005)	0.041 (0.001)	0.054 (0.002)
VIII. Less Than College						IX. College					
[1,7]	0.191 (0.002)	0.313 (0.007)	0.277 (0.006)	0.150 (0.006)	0.173 (0.005)	[1,7]	0.193 (0.004)	0.324 (0.013)	0.250 (0.008)	0.133 (0.008)	0.172 (0.008)
[1,4]	0.102 (0.002)	0.113 (0.004)	0.141 (0.006)	0.060 (0.004)	0.065 (0.003)	[1,4]	0.102 (0.003)	0.104 (0.005)	0.115 (0.007)	0.046 (0.004)	0.056 (0.003)
[4,5]	0.097 (0.002)	0.092 (0.003)	0.115 (0.008)	0.043 (0.003)	0.051 (0.002)	[4,5]	0.097 (0.003)	0.095 (0.006)	0.088 (0.007)	0.032 (0.002)	0.047 (0.003)
[5,6]	0.079 (0.001)	0.058 (0.002)	0.074 (0.003)	0.024 (0.001)	0.031 (0.002)	[5,6]	0.083 (0.002)	0.066 (0.004)	0.067 (0.004)	0.024 (0.001)	0.033 (0.002)
[6,7]	0.109 (0.002)	0.103 (0.003)	0.153 (0.005)	0.040 (0.001)	0.052 (0.002)	[6,7]	0.115 (0.003)	0.118 (0.006)	0.143 (0.007)	0.045 (0.002)	0.058 (0.003)
X. Low SES						XI. High SES					
[1,7]	0.188 (0.004)	0.306 (0.012)	0.291 (0.010)	0.153 (0.009)	0.166 (0.008)	[1,7]	0.193 (0.003)	0.324 (0.009)	0.260 (0.006)	0.142 (0.006)	0.177 (0.006)
[1,4]	0.099 (0.003)	0.107 (0.006)	0.142 (0.009)	0.056 (0.004)	0.059 (0.003)	[1,4]	0.103 (0.002)	0.113 (0.004)	0.130 (0.005)	0.056 (0.003)	0.065 (0.003)
[4,5]	0.095 (0.002)	0.087 (0.004)	0.125 (0.014)	0.049 (0.006)	0.049 (0.003)	[4,5]	0.098 (0.002)	0.096 (0.004)	0.099 (0.006)	0.036 (0.002)	0.050 (0.002)
[5,6]	0.076 (0.002)	0.055 (0.003)	0.083 (0.006)	0.026 (0.003)	0.031 (0.003)	[5,6]	0.081 (0.001)	0.063 (0.002)	0.067 (0.003)	0.022 (0.001)	0.032 (0.001)
[6,7]	0.108 (0.003)	0.100 (0.005)	0.155 (0.009)	0.040 (0.002)	0.051 (0.003)	[6,7]	0.111 (0.002)	0.110 (0.003)	0.148 (0.005)	0.042 (0.001)	0.055 (0.002)

Table 2b. Mobility Measures: Percentile Height

	Bart	Spear	S-Theil	O-M(0)	R-M(0)		Bart	Spear	S-Theil	O-M(0)	R-M(0)
I. Full Sample											
[1,7]	0.180 (0.002)	0.287 (0.006)	0.207 (0.006)	0.111 (0.002)	0.130 (0.003)						
[1,4]	0.087 (0.001)	0.091 (0.003)	0.062 (0.002)	0.035 (0.002)	0.041 (0.002)						
[4,5]	0.082 (0.001)	0.080 (0.003)	0.072 (0.004)	0.031 (0.001)	0.034 (0.001)						
[5,6]	0.090 (0.001)	0.088 (0.003)	0.088 (0.005)	0.040 (0.002)	0.045 (0.002)						
[6,7]	0.153 (0.002)	0.211 (0.005)	0.172 (0.005)	0.074 (0.002)	0.092 (0.003)						
II. White						III. Non-White					
[1,7]	0.180 (0.003)	0.285 (0.008)	0.203 (0.008)	0.104 (0.003)	0.130 (0.004)	[1,7]	0.180 (0.003)	0.285 (0.010)	0.211 (0.009)	0.120 (0.004)	0.128 (0.005)
[1,4]	0.085 (0.002)	0.089 (0.004)	0.058 (0.002)	0.033 (0.002)	0.039 (0.002)	[1,4]	0.089 (0.002)	0.094 (0.005)	0.068 (0.004)	0.040 (0.003)	0.044 (0.003)
[4,5]	0.078 (0.002)	0.072 (0.003)	0.066 (0.005)	0.026 (0.001)	0.030 (0.001)	[4,5]	0.089 (0.002)	0.093 (0.005)	0.082 (0.007)	0.039 (0.002)	0.040 (0.002)
[5,6]	0.087 (0.002)	0.083 (0.004)	0.081 (0.006)	0.033 (0.003)	0.040 (0.003)	[5,6]	0.094 (0.002)	0.096 (0.005)	0.099 (0.008)	0.053 (0.005)	0.052 (0.004)
[6,7]	0.147 (0.002)	0.192 (0.006)	0.156 (0.006)	0.064 (0.002)	0.085 (0.003)	[6,7]	0.162 (0.003)	0.235 (0.009)	0.190 (0.008)	0.091 (0.003)	0.100 (0.004)
IV. Male						V. Female					
[1,7]	0.180 (0.003)	0.282 (0.009)	0.190 (0.008)	0.109 (0.004)	0.129 (0.004)	[1,7]	0.177 (0.003)	0.283 (0.008)	0.221 (0.007)	0.110 (0.004)	0.127 (0.004)
[1,4]	0.082 (0.002)	0.088 (0.005)	0.057 (0.004)	0.034 (0.003)	0.041 (0.003)	[1,4]	0.086 (0.002)	0.089 (0.005)	0.065 (0.003)	0.036 (0.002)	0.039 (0.002)
[4,5]	0.078 (0.002)	0.073 (0.004)	0.067 (0.005)	0.027 (0.001)	0.032 (0.002)	[4,5]	0.085 (0.002)	0.084 (0.004)	0.076 (0.005)	0.034 (0.002)	0.035 (0.002)
[5,6]	0.076 (0.002)	0.070 (0.004)	0.079 (0.006)	0.032 (0.003)	0.037 (0.003)	[5,6]	0.102 (0.002)	0.104 (0.004)	0.097 (0.006)	0.048 (0.003)	0.051 (0.003)
[6,7]	0.131 (0.002)	0.150 (0.005)	0.138 (0.006)	0.055 (0.002)	0.069 (0.003)	[6,7]	0.175 (0.003)	0.259 (0.008)	0.199 (0.008)	0.092 (0.003)	0.111 (0.004)

Notes: See Table 2a for details.

Table 2b (cont.). Mobility Measures: Percentile Height

	Bart	Spear	S-Theil	O-M(0)	R-M(0)		Bart	Spear	S-Theil	O-M(0)	R-M(0)
VI. Urban						VII. Non-Urban					
[1,7]	0.186 (0.004)	0.305 (0.011)	0.214 (0.010)	0.123 (0.005)	0.140 (0.006)	[1,7]	0.177 (0.003)	0.277 (0.008)	0.203 (0.007)	0.104 (0.003)	0.125 (0.004)
[1,4]	0.086 (0.002)	0.085 (0.004)	0.058 (0.003)	0.033 (0.002)	0.037 (0.003)	[1,4]	0.087 (0.002)	0.095 (0.004)	0.065 (0.003)	0.037 (0.002)	0.043 (0.003)
[4,5]	0.086 (0.002)	0.086 (0.005)	0.074 (0.007)	0.033 (0.002)	0.036 (0.002)	[4,5]	0.080 (0.002)	0.076 (0.004)	0.072 (0.004)	0.030 (0.001)	0.033 (0.002)
[5,6]	0.095 (0.002)	0.097 (0.005)	0.091 (0.008)	0.045 (0.004)	0.048 (0.004)	[5,6]	0.088 (0.002)	0.083 (0.004)	0.087 (0.006)	0.038 (0.003)	0.043 (0.003)
[6,7]	0.161 (0.003)	0.235 (0.008)	0.182 (0.007)	0.086 (0.004)	0.104 (0.004)	[6,7]	0.149 (0.002)	0.198 (0.006)	0.167 (0.006)	0.068 (0.002)	0.085 (0.003)
VIII. Less Than College						IX. College					
[1,7]	0.180 (0.002)	0.287 (0.007)	0.212 (0.007)	0.115 (0.003)	0.130 (0.004)	[1,7]	0.183 (0.004)	0.290 (0.012)	0.193 (0.009)	0.101 (0.004)	0.133 (0.006)
[1,4]	0.087 (0.002)	0.091 (0.004)	0.063 (0.002)	0.037 (0.002)	0.041 (0.002)	[1,4]	0.086 (0.003)	0.093 (0.007)	0.060 (0.004)	0.031 (0.002)	0.041 (0.004)
[4,5]	0.082 (0.001)	0.080 (0.003)	0.073 (0.004)	0.032 (0.001)	0.034 (0.002)	[4,5]	0.081 (0.003)	0.081 (0.006)	0.070 (0.008)	0.028 (0.002)	0.035 (0.003)
[5,6]	0.089 (0.002)	0.086 (0.003)	0.090 (0.005)	0.042 (0.003)	0.045 (0.003)	[5,6]	0.092 (0.003)	0.094 (0.006)	0.082 (0.009)	0.035 (0.004)	0.045 (0.003)
[6,7]	0.154 (0.002)	0.211 (0.006)	0.174 (0.006)	0.077 (0.002)	0.091 (0.002)	[6,7]	0.150 (0.004)	0.209 (0.010)	0.165 (0.010)	0.066 (0.004)	0.094 (0.006)
X. Low SES						XI. High SES					
[1,7]	0.182 (0.004)	0.295 (0.011)	0.218 (0.011)	0.128 (0.005)	0.131 (0.005)	[1,7]	0.180 (0.002)	0.283 (0.007)	0.201 (0.007)	0.103 (0.003)	0.131 (0.004)
[1,4]	0.088 (0.002)	0.095 (0.006)	0.065 (0.004)	0.041 (0.003)	0.042 (0.003)	[1,4]	0.086 (0.002)	0.089 (0.004)	0.061 (0.003)	0.033 (0.002)	0.041 (0.003)
[4,5]	0.082 (0.002)	0.078 (0.005)	0.073 (0.007)	0.035 (0.002)	0.033 (0.002)	[4,5]	0.082 (0.002)	0.081 (0.004)	0.072 (0.005)	0.029 (0.001)	0.034 (0.002)
[5,6]	0.087 (0.002)	0.080 (0.005)	0.090 (0.007)	0.043 (0.003)	0.040 (0.003)	[5,6]	0.091 (0.002)	0.092 (0.004)	0.087 (0.006)	0.039 (0.003)	0.048 (0.003)
[6,7]	0.155 (0.003)	0.219 (0.009)	0.180 (0.008)	0.088 (0.004)	0.094 (0.004)	[6,7]	0.152 (0.002)	0.206 (0.006)	0.167 (0.006)	0.068 (0.002)	0.091 (0.003)

Table 2c. Mobility Measures: Percentile BMI

	Bart	Spear	S-Theil	O-M(0)	R-M(0)		Bart	Spear	S-Theil	O-M(0)	R-M(0)
I. Full Sample											
[1,7]	0.217 (0.003)	0.405 (0.008)	0.498 (0.009)	0.358 (0.021)	0.243 (0.005)						
[1,4]	0.147 (0.002)	0.218 (0.006)	0.437 (0.011)	0.221 (0.013)	0.138 (0.004)						
[4,5]	0.125 (0.002)	0.155 (0.004)	0.313 (0.017)	0.113 (0.010)	0.101 (0.004)						
[5,6]	0.094 (0.001)	0.086 (0.003)	0.170 (0.011)	0.042 (0.003)	0.051 (0.002)						
[6,7]	0.118 (0.002)	0.126 (0.003)	0.230 (0.011)	0.050 (0.002)	0.067 (0.002)						
II. White						III. Non-White					
[1,7]	0.224 (0.003)	0.427 (0.011)	0.493 (0.011)	0.390 (0.028)	0.255 (0.008)	[1,7]	0.207 (0.004)	0.376 (0.012)	0.510 (0.018)	0.306 (0.027)	0.224 (0.008)
[1,4]	0.151 (0.003)	0.231 (0.007)	0.435 (0.014)	0.234 (0.017)	0.144 (0.005)	[1,4]	0.140 (0.003)	0.199 (0.009)	0.443 (0.021)	0.199 (0.018)	0.128 (0.006)
[4,5]	0.129 (0.002)	0.167 (0.006)	0.307 (0.024)	0.113 (0.013)	0.105 (0.005)	[4,5]	0.119 (0.003)	0.136 (0.006)	0.326 (0.026)	0.113 (0.017)	0.092 (0.005)
[5,6]	0.097 (0.002)	0.091 (0.003)	0.160 (0.012)	0.042 (0.004)	0.053 (0.002)	[5,6]	0.091 (0.002)	0.080 (0.004)	0.193 (0.023)	0.042 (0.006)	0.047 (0.003)
[6,7]	0.122 (0.002)	0.137 (0.004)	0.227 (0.013)	0.053 (0.002)	0.072 (0.003)	[6,7]	0.111 (0.002)	0.112 (0.005)	0.237 (0.021)	0.045 (0.003)	0.060 (0.003)
IV. Male						V. Female					
[1,7]	0.221 (0.003)	0.416 (0.012)	0.532 (0.014)	0.408 (0.035)	0.250 (0.008)	[1,7]	0.212 (0.003)	0.391 (0.011)	0.458 (0.010)	0.307 (0.023)	0.233 (0.007)
[1,4]	0.152 (0.003)	0.233 (0.009)	0.467 (0.018)	0.245 (0.022)	0.145 (0.006)	[1,4]	0.142 (0.003)	0.203 (0.007)	0.403 (0.013)	0.195 (0.013)	0.130 (0.005)
[4,5]	0.129 (0.002)	0.167 (0.006)	0.340 (0.029)	0.129 (0.018)	0.108 (0.005)	[4,5]	0.121 (0.002)	0.143 (0.006)	0.287 (0.020)	0.096 (0.009)	0.093 (0.004)
[5,6]	0.094 (0.002)	0.087 (0.004)	0.180 (0.015)	0.039 (0.004)	0.052 (0.003)	[5,6]	0.095 (0.002)	0.085 (0.003)	0.162 (0.017)	0.044 (0.006)	0.050 (0.003)
[6,7]	0.113 (0.002)	0.120 (0.004)	0.243 (0.019)	0.048 (0.002)	0.064 (0.003)	[6,7]	0.120 (0.002)	0.128 (0.005)	0.210 (0.011)	0.052 (0.002)	0.068 (0.003)

Notes: See Table 2a for details.

Table 2c (cont.). Mobility Measures: Percentile BMI

	Bart	Spear	S-Theil	O-M(0)	R-M(0)		Bart	Spear	S-Theil	O-M(0)	R-M(0)
VI. Urban						VII. Non-Urban					
[1,7]	0.213 (0.004)	0.391 (0.013)	0.477 (0.014)	0.308 (0.032)	0.233 (0.010)	[1,7]	0.219 (0.003)	0.413 (0.011)	0.509 (0.013)	0.385 (0.028)	0.247 (0.007)
[1,4]	0.145 (0.003)	0.209 (0.009)	0.411 (0.019)	0.194 (0.021)	0.131 (0.006)	[1,4]	0.148 (0.003)	0.224 (0.008)	0.451 (0.016)	0.236 (0.018)	0.141 (0.005)
[4,5]	0.122 (0.003)	0.150 (0.007)	0.326 (0.032)	0.124 (0.025)	0.101 (0.007)	[4,5]	0.127 (0.002)	0.158 (0.005)	0.306 (0.021)	0.107 (0.010)	0.101 (0.004)
[5,6]	0.092 (0.002)	0.083 (0.004)	0.192 (0.022)	0.050 (0.007)	0.050 (0.003)	[5,6]	0.095 (0.002)	0.088 (0.003)	0.157 (0.010)	0.037 (0.002)	0.051 (0.002)
[6,7]	0.117 (0.002)	0.124 (0.005)	0.213 (0.012)	0.050 (0.003)	0.066 (0.003)	[6,7]	0.118 (0.002)	0.127 (0.004)	0.239 (0.017)	0.050 (0.002)	0.068 (0.002)
VIII. Less Than College						IX. College					
[1,7]	0.215 (0.003)	0.397 (0.009)	0.510 (0.012)	0.364 (0.025)	0.241 (0.006)	[1,7]	0.222 (0.005)	0.424 (0.016)	0.472 (0.015)	0.337 (0.033)	0.240 (0.010)
[1,4]	0.145 (0.002)	0.214 (0.007)	0.449 (0.015)	0.225 (0.017)	0.137 (0.005)	[1,4]	0.150 (0.004)	0.228 (0.010)	0.407 (0.021)	0.209 (0.020)	0.139 (0.007)
[4,5]	0.125 (0.002)	0.152 (0.005)	0.336 (0.023)	0.123 (0.015)	0.100 (0.004)	[4,5]	0.127 (0.003)	0.163 (0.008)	0.257 (0.020)	0.085 (0.007)	0.099 (0.006)
[5,6]	0.093 (0.001)	0.082 (0.003)	0.174 (0.013)	0.039 (0.004)	0.048 (0.002)	[5,6]	0.102 (0.003)	0.102 (0.005)	0.165 (0.017)	0.049 (0.007)	0.058 (0.004)
[6,7]	0.115 (0.002)	0.121 (0.004)	0.232 (0.016)	0.046 (0.002)	0.065 (0.002)	[6,7]	0.127 (0.003)	0.149 (0.007)	0.230 (0.015)	0.061 (0.003)	0.076 (0.004)
X. Low SES						XI. High SES					
[1,7]	0.214 (0.004)	0.389 (0.014)	0.501 (0.017)	0.334 (0.032)	0.234 (0.010)	[1,7]	0.218 (0.003)	0.414 (0.010)	0.499 (0.011)	0.370 (0.027)	0.246 (0.007)
[1,4]	0.144 (0.003)	0.211 (0.010)	0.428 (0.018)	0.201 (0.017)	0.132 (0.007)	[1,4]	0.149 (0.003)	0.223 (0.008)	0.442 (0.014)	0.230 (0.016)	0.140 (0.005)
[4,5]	0.123 (0.003)	0.145 (0.007)	0.318 (0.031)	0.124 (0.021)	0.100 (0.006)	[4,5]	0.127 (0.002)	0.160 (0.006)	0.313 (0.021)	0.107 (0.012)	0.100 (0.004)
[5,6]	0.090 (0.002)	0.077 (0.004)	0.144 (0.012)	0.032 (0.003)	0.044 (0.003)	[5,6]	0.097 (0.002)	0.093 (0.003)	0.182 (0.015)	0.047 (0.005)	0.054 (0.002)
[6,7]	0.114 (0.003)	0.116 (0.005)	0.248 (0.025)	0.043 (0.003)	0.062 (0.003)	[6,7]	0.121 (0.002)	0.135 (0.004)	0.224 (0.012)	0.054 (0.002)	0.071 (0.002)

Table 3a. Upward Mobility Measures: Percentile Weight

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
I. Full Sample											
[1,7]	0.457	0.398	0.314	0.194	0.038						
	(0.011)	(0.012)	(0.011)	(0.009)	(0.004)						
[1,4]	0.217	0.225	0.222	0.120	0.008						
	(0.009)	(0.009)	(0.009)	(0.007)	(0.002)						
[4,5]	0.186	0.260	0.209	0.112	0.011						
	(0.008)	(0.010)	(0.009)	(0.007)	(0.003)						
[5,6]	0.146	0.227	0.192	0.105	0.006						
	(0.008)	(0.010)	(0.009)	(0.008)	(0.002)						
[6,7]	0.247	0.325	0.251	0.158	0.018						
	(0.009)	(0.011)	(0.010)	(0.009)	(0.003)						
II. White						III. Non-White					
[1,7]	0.472	0.404	0.313	0.194	0.042	[1,7]	0.429	0.387	0.309	0.191	0.033
	(0.013)	(0.015)	(0.012)	(0.011)	(0.006)		(0.016)	(0.018)	(0.017)	(0.015)	(0.007)
[1,4]	0.225	0.235	0.221	0.127	0.012	[1,4]	0.202	0.217	0.208	0.095	0.012
	(0.011)	(0.013)	(0.012)	(0.009)	(0.004)		(0.014)	(0.018)	(0.016)	(0.013)	(0.005)
[4,5]	0.186	0.269	0.209	0.130	0.011	[4,5]	0.182	0.259	0.188	0.103	0.005
	(0.011)	(0.012)	(0.011)	(0.010)	(0.003)		(0.015)	(0.017)	(0.015)	(0.013)	(0.003)
[5,6]	0.146	0.241	0.204	0.108	0.010	[5,6]	0.148	0.220	0.171	0.100	0.000
	(0.010)	(0.013)	(0.012)	(0.011)	(0.004)		(0.013)	(0.016)	(0.015)	(0.012)	(0.002)
[6,7]	0.254	0.317	0.267	0.177	0.015	[6,7]	0.233	0.296	0.238	0.126	0.007
	(0.012)	(0.014)	(0.014)	(0.011)	(0.005)		(0.016)	(0.019)	(0.016)	(0.013)	(0.006)
IV. Male						V. Female					
[1,7]	0.479	0.410	0.312	0.204	0.041	[1,7]	0.432	0.392	0.314	0.188	0.028
	(0.015)	(0.016)	(0.015)	(0.013)	(0.007)		(0.016)	(0.016)	(0.018)	(0.012)	(0.006)
[1,4]	0.222	0.227	0.232	0.131	0.011	[1,4]	0.218	0.223	0.216	0.107	0.006
	(0.013)	(0.015)	(0.014)	(0.013)	(0.003)		(0.013)	(0.013)	(0.013)	(0.010)	(0.003)
[4,5]	0.185	0.268	0.216	0.111	0.010	[4,5]	0.171	0.263	0.205	0.120	0.011
	(0.012)	(0.014)	(0.013)	(0.010)	(0.004)		(0.013)	(0.015)	(0.013)	(0.011)	(0.005)
[5,6]	0.149	0.240	0.167	0.104	0.008	[5,6]	0.158	0.211	0.187	0.114	0.002
	(0.011)	(0.014)	(0.013)	(0.010)	(0.003)		(0.011)	(0.014)	(0.013)	(0.012)	(0.003)
[6,7]	0.244	0.301	0.247	0.139	0.012	[6,7]	0.223	0.331	0.265	0.176	0.013
	(0.015)	(0.015)	(0.015)	(0.013)	(0.004)		(0.013)	(0.015)	(0.014)	(0.013)	(0.004)

Notes: Left column denotes the time span over which mobility is computed. Period 1 = fall kindergarten; Period 4 = spring 1st grade; Period 5 = spring 3rd grade; Period 6 = spring 5th grade; and, Period 7 = spring 8th grade. Q1 - Q5 refers to the first through fifth quantiles in the initial period. Bootstrap standard errors based on 250 repetitions (clustered at the child-level) in parentheses. N = 8370 (full sample), 5330 (white sample), 3040 (non-white sample), 4230 (male sample), 4140 (female sample), 3030 (urban sample), and 5340 (non-urban sample) with sample sizes rounded to the nearest 10 per NCES restricted data regulations. See text for definition of mobility measures ($\delta = 0.10$).

Table 3a (cont.). Upward Mobility Measures: Percentile Weight

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VI. Urban						VII. Non-Urban					
[1,7]	0.451	0.409	0.330	0.206	0.045	[1,7]	0.464	0.384	0.305	0.189	0.033
	(0.018)	(0.019)	(0.020)	(0.016)	(0.008)		(0.013)	(0.015)	(0.013)	(0.010)	(0.005)
[1,4]	0.206	0.214	0.219	0.125	0.012	[1,4]	0.225	0.229	0.217	0.123	0.005
	(0.015)	(0.016)	(0.016)	(0.013)	(0.005)		(0.013)	(0.013)	(0.011)	(0.010)	(0.003)
[4,5]	0.169	0.274	0.200	0.107	0.008	[4,5]	0.196	0.251	0.210	0.116	0.009
	(0.013)	(0.018)	(0.015)	(0.014)	(0.005)		(0.010)	(0.013)	(0.012)	(0.010)	(0.003)
[5,6]	0.145	0.201	0.191	0.097	0.000	[5,6]	0.150	0.241	0.194	0.103	0.008
	(0.013)	(0.016)	(0.016)	(0.013)	(0.002)		(0.011)	(0.011)	(0.011)	(0.010)	(0.003)
[6,7]	0.229	0.335	0.231	0.162	0.015	[6,7]	0.257	0.315	0.262	0.152	0.020
	(0.017)	(0.018)	(0.017)	(0.015)	(0.006)		(0.013)	(0.013)	(0.012)	(0.010)	(0.004)
VIII. Less Than College						IX. College					
[1,7]	0.455	0.383	0.306	0.197	0.038	[1,7]	0.466	0.415	0.302	0.209	0.039
	(0.012)	(0.013)	(0.012)	(0.010)	(0.005)		(0.020)	(0.021)	(0.019)	(0.017)	(0.008)
[1,4]	0.219	0.228	0.214	0.112	0.008	[1,4]	0.210	0.215	0.236	0.136	0.015
	(0.011)	(0.011)	(0.010)	(0.008)	(0.003)		(0.017)	(0.018)	(0.018)	(0.015)	(0.006)
[4,5]	0.188	0.263	0.210	0.115	0.008	[4,5]	0.173	0.262	0.172	0.112	0.013
	(0.010)	(0.011)	(0.011)	(0.010)	(0.003)		(0.017)	(0.019)	(0.018)	(0.014)	(0.006)
[5,6]	0.149	0.218	0.182	0.103	0.004	[5,6]	0.142	0.215	0.188	0.112	0.004
	(0.010)	(0.011)	(0.011)	(0.009)	(0.002)		(0.014)	(0.018)	(0.017)	(0.016)	(0.004)
[6,7]	0.247	0.307	0.253	0.157	0.012	[6,7]	0.249	0.328	0.294	0.190	0.009
	(0.012)	(0.012)	(0.011)	(0.011)	(0.004)		(0.018)	(0.025)	(0.019)	(0.017)	(0.006)
X. Low SES						XI. High SES					
[1,7]	0.433	0.397	0.326	0.190	0.045	[1,7]	0.453	0.405	0.317	0.206	0.040
	(0.017)	(0.019)	(0.018)	(0.015)	(0.009)		(0.012)	(0.014)	(0.014)	(0.010)	(0.006)
[1,4]	0.206	0.239	0.215	0.104	0.009	[1,4]	0.219	0.226	0.221	0.127	0.011
	(0.015)	(0.018)	(0.017)	(0.014)	(0.005)		(0.011)	(0.012)	(0.011)	(0.010)	(0.003)
[4,5]	0.189	0.267	0.218	0.117	0.009	[4,5]	0.176	0.266	0.202	0.115	0.010
	(0.015)	(0.018)	(0.017)	(0.014)	(0.004)		(0.010)	(0.011)	(0.011)	(0.009)	(0.003)
[5,6]	0.158	0.215	0.141	0.102	0.006	[5,6]	0.145	0.231	0.206	0.112	0.008
	(0.015)	(0.017)	(0.016)	(0.014)	(0.004)		(0.011)	(0.011)	(0.011)	(0.010)	(0.003)
[6,7]	0.248	0.284	0.256	0.147	0.011	[6,7]	0.241	0.330	0.267	0.175	0.014
	(0.018)	(0.018)	(0.018)	(0.015)	(0.005)		(0.011)	(0.014)	(0.012)	(0.010)	(0.004)

Table 3b. Upward Mobility Measures: Percentile Height

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
I. Full Sample											
[1,7]	0.379 (0.011)	0.426 (0.011)	0.342 (0.011)	0.255 (0.010)	0.044 (0.005)						
[1,4]	0.107 (0.008)	0.187 (0.009)	0.176 (0.009)	0.122 (0.009)	0.013 (0.003)						
[4,5]	0.091 (0.007)	0.198 (0.009)	0.190 (0.011)	0.104 (0.008)	0.011 (0.003)						
[5,6]	0.141 (0.008)	0.202 (0.009)	0.198 (0.009)	0.136 (0.008)	0.015 (0.003)						
[6,7]	0.304 (0.011)	0.404 (0.010)	0.355 (0.010)	0.260 (0.010)	0.044 (0.005)						
II. White						III. Non-White					
[1,7]	0.388 (0.014)	0.417 (0.014)	0.343 (0.014)	0.260 (0.012)	0.044 (0.006)	[1,7]	0.371 (0.018)	0.413 (0.020)	0.369 (0.018)	0.227 (0.017)	0.038 (0.008)
[1,4]	0.102 (0.009)	0.182 (0.011)	0.178 (0.012)	0.130 (0.010)	0.017 (0.004)	[1,4]	0.125 (0.013)	0.189 (0.015)	0.175 (0.016)	0.112 (0.013)	0.010 (0.004)
[4,5]	0.080 (0.008)	0.189 (0.010)	0.176 (0.012)	0.096 (0.009)	0.009 (0.003)	[4,5]	0.120 (0.013)	0.199 (0.015)	0.216 (0.015)	0.129 (0.014)	0.013 (0.005)
[5,6]	0.132 (0.010)	0.179 (0.012)	0.225 (0.012)	0.132 (0.011)	0.012 (0.004)	[5,6]	0.156 (0.015)	0.236 (0.017)	0.189 (0.015)	0.116 (0.012)	0.021 (0.006)
[6,7]	0.287 (0.013)	0.379 (0.014)	0.344 (0.014)	0.251 (0.012)	0.039 (0.006)	[6,7]	0.312 (0.018)	0.447 (0.020)	0.347 (0.018)	0.253 (0.018)	0.045 (0.008)
IV. Male						V. Female					
[1,7]	0.419 (0.015)	0.418 (0.015)	0.353 (0.016)	0.261 (0.014)	0.039 (0.007)	[1,7]	0.356 (0.015)	0.419 (0.016)	0.335 (0.015)	0.237 (0.014)	0.045 (0.007)
[1,4]	0.106 (0.011)	0.176 (0.013)	0.163 (0.013)	0.105 (0.011)	0.014 (0.004)	[1,4]	0.104 (0.011)	0.215 (0.013)	0.186 (0.014)	0.117 (0.011)	0.015 (0.004)
[4,5]	0.090 (0.010)	0.184 (0.014)	0.160 (0.013)	0.091 (0.012)	0.006 (0.003)	[4,5]	0.092 (0.010)	0.212 (0.014)	0.191 (0.013)	0.125 (0.012)	0.019 (0.005)
[5,6]	0.096 (0.009)	0.160 (0.012)	0.165 (0.015)	0.114 (0.011)	0.012 (0.004)	[5,6]	0.174 (0.012)	0.249 (0.013)	0.247 (0.014)	0.157 (0.012)	0.017 (0.005)
[6,7]	0.269 (0.014)	0.352 (0.015)	0.308 (0.015)	0.198 (0.013)	0.033 (0.006)	[6,7]	0.348 (0.017)	0.455 (0.017)	0.404 (0.017)	0.294 (0.015)	0.054 (0.010)

Notes: See Table 3a.

Table 3b (cont.). Upward Mobility Measures: Percentile Height

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VI. Urban						VII. Non-Urban					
[1,7]	0.399 (0.019)	0.437 (0.019)	0.355 (0.018)	0.243 (0.016)	0.048 (0.008)	[1,7]	0.373 (0.014)	0.420 (0.014)	0.345 (0.013)	0.261 (0.013)	0.032 (0.006)
[1,4]	0.097 (0.012)	0.206 (0.017)	0.185 (0.017)	0.109 (0.013)	0.020 (0.006)	[1,4]	0.112 (0.009)	0.178 (0.011)	0.170 (0.011)	0.125 (0.012)	0.009 (0.003)
[4,5]	0.086 (0.012)	0.200 (0.016)	0.204 (0.014)	0.104 (0.012)	0.020 (0.005)	[4,5]	0.096 (0.008)	0.192 (0.012)	0.187 (0.012)	0.107 (0.010)	0.006 (0.003)
[5,6]	0.135 (0.014)	0.230 (0.016)	0.221 (0.017)	0.139 (0.014)	0.022 (0.007)	[5,6]	0.140 (0.010)	0.199 (0.012)	0.185 (0.012)	0.122 (0.009)	0.015 (0.004)
[6,7]	0.328 (0.019)	0.435 (0.019)	0.365 (0.018)	0.254 (0.017)	0.045 (0.009)	[6,7]	0.291 (0.012)	0.391 (0.014)	0.344 (0.013)	0.258 (0.012)	0.048 (0.008)
VIII. Less Than College						IX. College					
[1,7]	0.378 (0.013)	0.421 (0.013)	0.342 (0.012)	0.257 (0.011)	0.046 (0.006)	[1,7]	0.442 (0.019)	0.443 (0.023)	0.334 (0.020)	0.253 (0.019)	0.028 (0.009)
[1,4]	0.109 (0.008)	0.192 (0.010)	0.176 (0.010)	0.119 (0.011)	0.016 (0.004)	[1,4]	0.111 (0.014)	0.175 (0.019)	0.191 (0.020)	0.120 (0.016)	0.013 (0.005)
[4,5]	0.094 (0.008)	0.201 (0.011)	0.190 (0.010)	0.109 (0.009)	0.013 (0.004)	[4,5]	0.082 (0.013)	0.187 (0.020)	0.172 (0.017)	0.109 (0.014)	0.013 (0.005)
[5,6]	0.140 (0.009)	0.206 (0.011)	0.196 (0.010)	0.128 (0.010)	0.014 (0.004)	[5,6]	0.135 (0.015)	0.224 (0.019)	0.193 (0.020)	0.139 (0.015)	0.017 (0.006)
[6,7]	0.306 (0.013)	0.409 (0.014)	0.344 (0.013)	0.267 (0.012)	0.049 (0.006)	[6,7]	0.303 (0.020)	0.394 (0.023)	0.352 (0.022)	0.226 (0.020)	0.034 (0.009)
X. Low SES						XI. High SES					
[1,7]	0.402 (0.018)	0.407 (0.019)	0.345 (0.019)	0.265 (0.018)	0.051 (0.009)	[1,7]	0.396 (0.013)	0.425 (0.013)	0.347 (0.011)	0.242 (0.012)	0.037 (0.005)
[1,4]	0.114 (0.014)	0.185 (0.017)	0.170 (0.016)	0.117 (0.016)	0.009 (0.004)	[1,4]	0.113 (0.010)	0.188 (0.011)	0.181 (0.012)	0.126 (0.010)	0.014 (0.004)
[4,5]	0.101 (0.014)	0.210 (0.018)	0.199 (0.017)	0.130 (0.016)	0.023 (0.007)	[4,5]	0.089 (0.008)	0.196 (0.011)	0.189 (0.011)	0.088 (0.009)	0.011 (0.003)
[5,6]	0.160 (0.015)	0.204 (0.017)	0.173 (0.017)	0.134 (0.014)	0.011 (0.005)	[5,6]	0.131 (0.009)	0.208 (0.011)	0.221 (0.011)	0.124 (0.010)	0.018 (0.004)
[6,7]	0.305 (0.019)	0.422 (0.018)	0.339 (0.019)	0.252 (0.017)	0.055 (0.009)	[6,7]	0.302 (0.013)	0.402 (0.015)	0.354 (0.013)	0.262 (0.012)	0.038 (0.005)

Table 3c. Upward Mobility Measures: Percentile BMI

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
I. Full Sample											
[1,7]	0.543	0.409	0.311	0.189	0.032						
	(0.011)	(0.012)	(0.011)	(0.009)	(0.004)						
[1,4]	0.380	0.315	0.244	0.146	0.014						
	(0.010)	(0.010)	(0.010)	(0.008)	(0.003)						
[4,5]	0.329	0.274	0.225	0.118	0.013						
	(0.010)	(0.010)	(0.009)	(0.007)	(0.003)						
[5,6]	0.224	0.235	0.196	0.115	0.010						
	(0.009)	(0.009)	(0.010)	(0.008)	(0.003)						
[6,7]	0.292	0.319	0.256	0.160	0.016						
	(0.011)	(0.011)	(0.010)	(0.009)	(0.003)						
II. White						III. Non-White					
[1,7]	0.560	0.402	0.302	0.196	0.034	[1,7]	0.521	0.399	0.312	0.173	0.033
	(0.014)	(0.013)	(0.013)	(0.011)	(0.005)		(0.017)	(0.019)	(0.017)	(0.016)	(0.007)
[1,4]	0.386	0.320	0.230	0.160	0.017	[1,4]	0.363	0.312	0.259	0.130	0.008
	(0.012)	(0.014)	(0.012)	(0.010)	(0.004)		(0.016)	(0.017)	(0.016)	(0.014)	(0.005)
[4,5]	0.324	0.284	0.237	0.134	0.009	[4,5]	0.333	0.273	0.209	0.107	0.010
	(0.012)	(0.014)	(0.013)	(0.010)	(0.003)		(0.017)	(0.017)	(0.014)	(0.011)	(0.004)
[5,6]	0.229	0.240	0.206	0.115	0.011	[5,6]	0.225	0.222	0.163	0.117	0.012
	(0.010)	(0.013)	(0.013)	(0.010)	(0.004)		(0.016)	(0.016)	(0.014)	(0.013)	(0.005)
[6,7]	0.303	0.333	0.271	0.156	0.022	[6,7]	0.291	0.292	0.245	0.143	0.015
	(0.013)	(0.013)	(0.013)	(0.011)	(0.005)		(0.017)	(0.017)	(0.016)	(0.014)	(0.005)
IV. Male						V. Female					
[1,7]	0.557	0.389	0.319	0.183	0.024	[1,7]	0.517	0.423	0.307	0.192	0.034
	(0.014)	(0.014)	(0.015)	(0.014)	(0.005)		(0.016)	(0.016)	(0.015)	(0.013)	(0.006)
[1,4]	0.405	0.323	0.251	0.148	0.011	[1,4]	0.356	0.313	0.232	0.156	0.016
	(0.014)	(0.015)	(0.014)	(0.012)	(0.004)		(0.014)	(0.015)	(0.014)	(0.014)	(0.005)
[4,5]	0.321	0.288	0.213	0.117	0.015	[4,5]	0.324	0.259	0.233	0.120	0.011
	(0.013)	(0.014)	(0.013)	(0.011)	(0.004)		(0.014)	(0.014)	(0.013)	(0.011)	(0.004)
[5,6]	0.229	0.219	0.183	0.114	0.013	[5,6]	0.221	0.250	0.205	0.111	0.004
	(0.013)	(0.014)	(0.014)	(0.012)	(0.004)		(0.014)	(0.014)	(0.015)	(0.012)	(0.003)
[6,7]	0.275	0.322	0.251	0.137	0.014	[6,7]	0.291	0.324	0.266	0.164	0.016
	(0.014)	(0.014)	(0.014)	(0.012)	(0.004)		(0.015)	(0.015)	(0.015)	(0.012)	(0.005)

Notes: See Table 3a.

Table 3c (cont.). Upward Mobility Measures: Percentile BMI

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VI. Urban						VII. Non-Urban					
[1,7]	0.528 (0.016)	0.404 (0.018)	0.329 (0.018)	0.165 (0.014)	0.036 (0.007)	[1,7]	0.546 (0.012)	0.413 (0.013)	0.297 (0.014)	0.204 (0.011)	0.030 (0.005)
[1,4]	0.366 (0.016)	0.320 (0.019)	0.261 (0.017)	0.147 (0.015)	0.012 (0.005)	[1,4]	0.387 (0.012)	0.323 (0.013)	0.236 (0.012)	0.145 (0.011)	0.012 (0.003)
[4,5]	0.322 (0.016)	0.279 (0.018)	0.223 (0.016)	0.104 (0.013)	0.013 (0.005)	[4,5]	0.336 (0.012)	0.275 (0.013)	0.224 (0.011)	0.129 (0.010)	0.010 (0.003)
[5,6]	0.188 (0.015)	0.253 (0.018)	0.180 (0.015)	0.102 (0.014)	0.010 (0.004)	[5,6]	0.246 (0.012)	0.231 (0.012)	0.204 (0.012)	0.119 (0.011)	0.011 (0.003)
[6,7]	0.287 (0.016)	0.323 (0.017)	0.265 (0.017)	0.157 (0.014)	0.020 (0.005)	[6,7]	0.292 (0.014)	0.320 (0.013)	0.257 (0.013)	0.158 (0.011)	0.014 (0.004)
VIII. Less Than College						IX. College					
[1,7]	0.531 (0.013)	0.405 (0.012)	0.305 (0.012)	0.175 (0.012)	0.030 (0.005)	[1,7]	0.554 (0.022)	0.437 (0.021)	0.277 (0.020)	0.196 (0.018)	0.032 (0.009)
[1,4]	0.378 (0.011)	0.311 (0.012)	0.254 (0.012)	0.130 (0.011)	0.013 (0.003)	[1,4]	0.388 (0.020)	0.338 (0.022)	0.210 (0.019)	0.174 (0.015)	0.026 (0.007)
[4,5]	0.333 (0.012)	0.284 (0.011)	0.213 (0.012)	0.117 (0.009)	0.012 (0.003)	[4,5]	0.309 (0.019)	0.290 (0.020)	0.234 (0.019)	0.101 (0.018)	0.015 (0.005)
[5,6]	0.219 (0.011)	0.236 (0.011)	0.189 (0.010)	0.112 (0.009)	0.011 (0.003)	[5,6]	0.236 (0.018)	0.262 (0.018)	0.210 (0.017)	0.123 (0.016)	0.013 (0.006)
[6,7]	0.290 (0.013)	0.306 (0.012)	0.266 (0.012)	0.159 (0.010)	0.011 (0.003)	[6,7]	0.320 (0.021)	0.338 (0.020)	0.298 (0.019)	0.153 (0.017)	0.017 (0.006)
X. Low SES						XI. High SES					
[1,7]	0.540 (0.019)	0.392 (0.020)	0.329 (0.020)	0.177 (0.016)	0.034 (0.007)	[1,7]	0.540 (0.013)	0.414 (0.013)	0.291 (0.013)	0.191 (0.011)	0.032 (0.005)
[1,4]	0.378 (0.015)	0.307 (0.019)	0.248 (0.018)	0.138 (0.014)	0.008 (0.004)	[1,4]	0.379 (0.012)	0.320 (0.013)	0.232 (0.012)	0.156 (0.011)	0.018 (0.004)
[4,5]	0.340 (0.016)	0.281 (0.017)	0.209 (0.016)	0.111 (0.012)	0.011 (0.005)	[4,5]	0.326 (0.012)	0.290 (0.014)	0.232 (0.011)	0.126 (0.010)	0.011 (0.003)
[5,6]	0.205 (0.018)	0.222 (0.019)	0.196 (0.016)	0.119 (0.014)	0.011 (0.005)	[5,6]	0.236 (0.011)	0.256 (0.012)	0.204 (0.012)	0.109 (0.010)	0.013 (0.003)
[6,7]	0.288 (0.020)	0.294 (0.018)	0.243 (0.018)	0.179 (0.016)	0.013 (0.005)	[6,7]	0.300 (0.012)	0.326 (0.013)	0.277 (0.013)	0.155 (0.010)	0.012 (0.004)

Table 4a. Downward Mobility Measures: Percentile Weight

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
I. Full Sample											
[1,7]	0.062	0.287	0.374	0.479	0.390						
	(0.005)	(0.011)	(0.011)	(0.011)	(0.010)						
[1,4]	0.022	0.169	0.250	0.280	0.108						
	(0.004)	(0.009)	(0.011)	(0.011)	(0.008)						
[4,5]	0.023	0.166	0.283	0.289	0.091						
	(0.004)	(0.009)	(0.010)	(0.011)	(0.008)						
[5,6]	0.016	0.134	0.228	0.191	0.067						
	(0.003)	(0.009)	(0.010)	(0.010)	(0.007)						
[6,7]	0.045	0.219	0.305	0.295	0.140						
	(0.005)	(0.009)	(0.011)	(0.011)	(0.008)						
II. White						III. Non-White					
[1,7]	0.066	0.281	0.389	0.501	0.400	[1,7]	0.056	0.291	0.345	0.467	0.364
	(0.006)	(0.014)	(0.014)	(0.015)	(0.014)		(0.008)	(0.017)	(0.018)	(0.018)	(0.018)
[1,4]	0.023	0.164	0.274	0.295	0.107	[1,4]	0.020	0.170	0.220	0.265	0.104
	(0.005)	(0.013)	(0.014)	(0.014)	(0.009)		(0.005)	(0.015)	(0.020)	(0.019)	(0.013)
[4,5]	0.022	0.163	0.295	0.304	0.116	[4,5]	0.026	0.171	0.273	0.245	0.067
	(0.004)	(0.009)	(0.014)	(0.014)	(0.011)		(0.007)	(0.015)	(0.019)	(0.023)	(0.011)
[5,6]	0.014	0.138	0.239	0.203	0.078	[5,6]	0.018	0.134	0.194	0.169	0.046
	(0.004)	(0.011)	(0.013)	(0.013)	(0.009)		(0.006)	(0.016)	(0.015)	(0.017)	(0.009)
[6,7]	0.045	0.229	0.307	0.310	0.148	[6,7]	0.028	0.219	0.286	0.263	0.135
	(0.006)	(0.012)	(0.014)	(0.013)	(0.012)		(0.008)	(0.017)	(0.017)	(0.017)	(0.013)
IV. Male						V. Female					
[1,7]	0.065	0.279	0.383	0.498	0.388	[1,7]	0.054	0.279	0.365	0.464	0.395
	(0.007)	(0.014)	(0.015)	(0.016)	(0.016)		(0.008)	(0.014)	(0.015)	(0.018)	(0.016)
[1,4]	0.020	0.165	0.260	0.304	0.125	[1,4]	0.029	0.178	0.240	0.259	0.092
	(0.005)	(0.015)	(0.013)	(0.015)	(0.012)		(0.006)	(0.013)	(0.017)	(0.016)	(0.012)
[4,5]	0.020	0.171	0.294	0.301	0.097	[4,5]	0.022	0.170	0.272	0.281	0.086
	(0.006)	(0.014)	(0.016)	(0.019)	(0.011)		(0.005)	(0.013)	(0.016)	(0.017)	(0.011)
[5,6]	0.009	0.119	0.234	0.169	0.065	[5,6]	0.023	0.161	0.219	0.194	0.074
	(0.004)	(0.012)	(0.015)	(0.013)	(0.009)		(0.006)	(0.014)	(0.015)	(0.014)	(0.009)
[6,7]	0.026	0.233	0.306	0.275	0.107	[6,7]	0.039	0.222	0.308	0.299	0.183
	(0.006)	(0.015)	(0.016)	(0.015)	(0.011)		(0.006)	(0.014)	(0.016)	(0.015)	(0.012)

Notes: Left column denotes the time span over which mobility is computed. Period 1 = fall kindergarten; Period 4 = spring 1st grade; Period 5 = spring 3rd grade; Period 6 = spring 5th grade; and, Period 7 = spring 8th grade. Q1 - Q5 refers to the first through fifth quantiles in the initial period. Bootstrap standard errors based on 250 repetitions (clustered at the child-level) in parentheses. N = 8370 (full sample), 5330 (white sample), 3040 (non-white sample), 4230 (male sample), 4140 (female sample), 3030 (urban sample), and 5340 (non-urban sample) with sample sizes rounded to the nearest 10 per NCES restricted data regulations. See text for definition of mobility measures ($\delta = 0.10$).

Table 4a (cont.). Downward Mobility Measures: Percentile Weight

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VI. Urban						VII. Non-Urban					
[1,7]	0.051 (0.008)	0.293 (0.018)	0.356 (0.018)	0.474 (0.019)	0.395 (0.019)	[1,7]	0.067 (0.007)	0.287 (0.013)	0.379 (0.015)	0.483 (0.014)	0.388 (0.014)
[1,4]	0.026 (0.007)	0.176 (0.015)	0.232 (0.020)	0.254 (0.018)	0.112 (0.014)	[1,4]	0.018 (0.005)	0.166 (0.012)	0.261 (0.014)	0.293 (0.015)	0.104 (0.010)
[4,5]	0.021 (0.006)	0.173 (0.015)	0.291 (0.019)	0.290 (0.022)	0.084 (0.013)	[4,5]	0.024 (0.005)	0.162 (0.011)	0.273 (0.013)	0.298 (0.013)	0.094 (0.010)
[5,6]	0.015 (0.005)	0.137 (0.015)	0.211 (0.016)	0.177 (0.015)	0.071 (0.012)	[5,6]	0.017 (0.005)	0.137 (0.011)	0.241 (0.013)	0.187 (0.012)	0.073 (0.008)
[6,7]	0.043 (0.009)	0.226 (0.015)	0.330 (0.018)	0.286 (0.018)	0.131 (0.015)	[6,7]	0.036 (0.006)	0.220 (0.012)	0.296 (0.014)	0.298 (0.012)	0.146 (0.010)
VIII. Less Than College						IX. College					
[1,7]	0.051 (0.006)	0.292 (0.011)	0.375 (0.012)	0.487 (0.014)	0.377 (0.013)	[1,7]	0.064 (0.013)	0.262 (0.020)	0.351 (0.020)	0.444 (0.020)	0.400 (0.021)
[1,4]	0.017 (0.004)	0.169 (0.011)	0.266 (0.012)	0.285 (0.014)	0.100 (0.009)	[1,4]	0.034 (0.008)	0.166 (0.017)	0.201 (0.019)	0.287 (0.019)	0.123 (0.015)
[4,5]	0.024 (0.004)	0.163 (0.012)	0.282 (0.013)	0.292 (0.012)	0.082 (0.009)	[4,5]	0.015 (0.006)	0.176 (0.018)	0.262 (0.023)	0.271 (0.022)	0.116 (0.015)
[5,6]	0.012 (0.004)	0.129 (0.011)	0.224 (0.011)	0.176 (0.011)	0.060 (0.007)	[5,6]	0.015 (0.007)	0.146 (0.018)	0.218 (0.018)	0.220 (0.021)	0.069 (0.012)
[6,7]	0.038 (0.007)	0.240 (0.012)	0.297 (0.012)	0.285 (0.012)	0.147 (0.011)	[6,7]	0.045 (0.010)	0.210 (0.018)	0.296 (0.019)	0.291 (0.019)	0.170 (0.019)
X. Low SES						XI. High SES					
[1,7]	0.058 (0.009)	0.279 (0.018)	0.374 (0.020)	0.475 (0.021)	0.367 (0.019)	[1,7]	0.063 (0.006)	0.284 (0.012)	0.375 (0.013)	0.466 (0.014)	0.396 (0.012)
[1,4]	0.019 (0.006)	0.173 (0.017)	0.245 (0.021)	0.271 (0.024)	0.106 (0.014)	[1,4]	0.023 (0.005)	0.167 (0.011)	0.253 (0.013)	0.288 (0.013)	0.109 (0.010)
[4,5]	0.023 (0.007)	0.183 (0.020)	0.276 (0.020)	0.277 (0.019)	0.066 (0.016)	[4,5]	0.024 (0.004)	0.167 (0.010)	0.279 (0.013)	0.289 (0.014)	0.103 (0.010)
[5,6]	0.017 (0.006)	0.124 (0.016)	0.215 (0.018)	0.166 (0.016)	0.062 (0.012)	[5,6]	0.015 (0.004)	0.140 (0.010)	0.225 (0.012)	0.200 (0.011)	0.073 (0.008)
[6,7]	0.028 (0.008)	0.235 (0.017)	0.299 (0.017)	0.286 (0.018)	0.128 (0.015)	[6,7]	0.046 (0.006)	0.221 (0.011)	0.314 (0.012)	0.300 (0.013)	0.140 (0.010)

Table 4b. Downward Mobility Measures: Percentile Height

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
I. Full Sample											
[1,7]	0.042	0.222	0.354	0.385	0.398						
	(0.005)	(0.010)	(0.012)	(0.011)	(0.011)						
[1,4]	0.011	0.114	0.180	0.185	0.134						
	(0.003)	(0.008)	(0.010)	(0.010)	(0.007)						
[4,5]	0.011	0.086	0.166	0.178	0.135						
	(0.003)	(0.007)	(0.010)	(0.009)	(0.008)						
[5,6]	0.011	0.131	0.212	0.215	0.118						
	(0.003)	(0.009)	(0.009)	(0.010)	(0.008)						
[6,7]	0.024	0.195	0.303	0.333	0.333						
	(0.004)	(0.008)	(0.012)	(0.011)	(0.010)						
II. White						III. Non-White					
[1,7]	0.046	0.236	0.352	0.376	0.405	[1,7]	0.041	0.220	0.356	0.402	0.388
	(0.006)	(0.013)	(0.015)	(0.013)	(0.013)		(0.007)	(0.016)	(0.019)	(0.022)	(0.018)
[1,4]	0.010	0.104	0.169	0.171	0.141	[1,4]	0.012	0.126	0.211	0.205	0.130
	(0.003)	(0.010)	(0.013)	(0.011)	(0.010)		(0.006)	(0.014)	(0.015)	(0.020)	(0.013)
[4,5]	0.010	0.096	0.168	0.170	0.117	[4,5]	0.015	0.084	0.168	0.194	0.149
	(0.003)	(0.009)	(0.012)	(0.012)	(0.009)		(0.005)	(0.012)	(0.015)	(0.016)	(0.014)
[5,6]	0.009	0.131	0.164	0.218	0.117	[5,6]	0.018	0.128	0.257	0.226	0.125
	(0.004)	(0.011)	(0.014)	(0.014)	(0.010)		(0.006)	(0.015)	(0.017)	(0.018)	(0.015)
[6,7]	0.024	0.208	0.312	0.333	0.317	[6,7]	0.028	0.177	0.314	0.348	0.359
	(0.005)	(0.012)	(0.015)	(0.014)	(0.012)		(0.007)	(0.014)	(0.017)	(0.017)	(0.017)
IV. Male						V. Female					
[1,7]	0.048	0.253	0.341	0.378	0.388	[1,7]	0.040	0.207	0.350	0.370	0.395
	(0.008)	(0.013)	(0.015)	(0.017)	(0.014)		(0.006)	(0.013)	(0.015)	(0.017)	(0.014)
[1,4]	0.008	0.099	0.152	0.163	0.139	[1,4]	0.011	0.106	0.182	0.185	0.132
	(0.003)	(0.010)	(0.015)	(0.015)	(0.011)		(0.004)	(0.010)	(0.013)	(0.015)	(0.011)
[4,5]	0.012	0.087	0.155	0.154	0.117	[4,5]	0.011	0.088	0.170	0.188	0.140
	(0.003)	(0.010)	(0.013)	(0.012)	(0.011)		(0.004)	(0.010)	(0.014)	(0.013)	(0.011)
[5,6]	0.011	0.110	0.159	0.168	0.081	[5,6]	0.013	0.166	0.242	0.265	0.164
	(0.003)	(0.012)	(0.014)	(0.013)	(0.009)		(0.004)	(0.013)	(0.014)	(0.016)	(0.013)
[6,7]	0.025	0.211	0.342	0.342	0.243	[6,7]	0.022	0.207	0.308	0.379	0.432
	(0.006)	(0.014)	(0.015)	(0.017)	(0.014)		(0.005)	(0.014)	(0.015)	(0.014)	(0.016)

Notes: See Table 4a.

Table 4b (cont.). Downward Mobility Measures: Percentile Height

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VI. Urban						VII. Non-Urban					
[1,7]	0.046	0.206	0.362	0.404	0.397	[1,7]	0.042	0.231	0.346	0.370	0.403
	(0.009)	(0.015)	(0.016)	(0.019)	(0.017)		(0.006)	(0.013)	(0.013)	(0.014)	(0.014)
[1,4]	0.017	0.117	0.193	0.195	0.134	[1,4]	0.010	0.106	0.176	0.179	0.137
	(0.008)	(0.013)	(0.015)	(0.016)	(0.013)		(0.004)	(0.010)	(0.012)	(0.012)	(0.009)
[4,5]	0.015	0.087	0.161	0.205	0.154	[4,5]	0.008	0.090	0.165	0.161	0.124
	(0.005)	(0.012)	(0.016)	(0.016)	(0.013)		(0.003)	(0.009)	(0.012)	(0.011)	(0.010)
[5,6]	0.012	0.137	0.216	0.248	0.126	[5,6]	0.014	0.129	0.200	0.208	0.113
	(0.007)	(0.017)	(0.016)	(0.019)	(0.012)		(0.004)	(0.011)	(0.012)	(0.014)	(0.010)
[6,7]	0.025	0.192	0.307	0.351	0.345	[6,7]	0.024	0.198	0.301	0.320	0.332
	(0.007)	(0.016)	(0.016)	(0.018)	(0.017)		(0.005)	(0.012)	(0.014)	(0.014)	(0.013)
VIII. Less Than College						IX. College					
[1,7]	0.036	0.219	0.353	0.378	0.408	[1,7]	0.045	0.240	0.356	0.396	0.357
	(0.005)	(0.012)	(0.013)	(0.012)	(0.012)		(0.011)	(0.018)	(0.021)	(0.021)	(0.020)
[1,4]	0.011	0.118	0.179	0.184	0.143	[1,4]	0.011	0.093	0.178	0.191	0.121
	(0.004)	(0.009)	(0.011)	(0.011)	(0.010)		(0.006)	(0.016)	(0.018)	(0.019)	(0.015)
[4,5]	0.007	0.092	0.169	0.176	0.136	[4,5]	0.015	0.080	0.178	0.180	0.132
	(0.002)	(0.009)	(0.011)	(0.011)	(0.009)		(0.006)	(0.013)	(0.019)	(0.017)	(0.015)
[5,6]	0.013	0.137	0.205	0.214	0.120	[5,6]	0.004	0.118	0.195	0.237	0.109
	(0.004)	(0.011)	(0.011)	(0.012)	(0.009)		(0.005)	(0.018)	(0.022)	(0.023)	(0.014)
[6,7]	0.025	0.193	0.309	0.329	0.348	[6,7]	0.028	0.198	0.292	0.344	0.295
	(0.004)	(0.011)	(0.012)	(0.012)	(0.012)		(0.007)	(0.018)	(0.021)	(0.020)	(0.020)
X. Low SES						XI. High SES					
[1,7]	0.036	0.209	0.335	0.359	0.421	[1,7]	0.045	0.233	0.350	0.399	0.385
	(0.008)	(0.017)	(0.021)	(0.022)	(0.020)		(0.007)	(0.012)	(0.013)	(0.013)	(0.013)
[1,4]	0.013	0.124	0.173	0.184	0.153	[1,4]	0.013	0.103	0.186	0.191	0.124
	(0.007)	(0.015)	(0.016)	(0.016)	(0.015)		(0.004)	(0.010)	(0.012)	(0.012)	(0.009)
[4,5]	0.008	0.100	0.152	0.168	0.134	[4,5]	0.008	0.089	0.176	0.176	0.133
	(0.004)	(0.014)	(0.016)	(0.017)	(0.014)		(0.003)	(0.008)	(0.011)	(0.011)	(0.009)
[5,6]	0.011	0.151	0.205	0.199	0.126	[5,6]	0.010	0.137	0.198	0.233	0.117
	(0.005)	(0.017)	(0.018)	(0.018)	(0.014)		(0.003)	(0.010)	(0.013)	(0.013)	(0.009)
[6,7]	0.021	0.193	0.297	0.335	0.338	[6,7]	0.026	0.201	0.303	0.335	0.330
	(0.007)	(0.016)	(0.016)	(0.019)	(0.016)		(0.005)	(0.012)	(0.013)	(0.013)	(0.012)

Table 4c. Downward Mobility Measures: Percentile BMI

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
I. Full Sample											
[1,7]	0.052	0.311	0.417	0.513	0.410						
	(0.005)	(0.011)	(0.011)	(0.011)	(0.011)						
[1,4]	0.046	0.245	0.361	0.361	0.186						
	(0.005)	(0.010)	(0.010)	(0.011)	(0.011)						
[4,5]	0.047	0.250	0.354	0.348	0.117						
	(0.005)	(0.010)	(0.012)	(0.011)	(0.008)						
[5,6]	0.035	0.206	0.253	0.222	0.090						
	(0.004)	(0.010)	(0.011)	(0.010)	(0.007)						
[6,7]	0.038	0.228	0.313	0.306	0.142						
	(0.005)	(0.010)	(0.010)	(0.010)	(0.009)						
II. White						III. Non-White					
[1,7]	0.046	0.325	0.431	0.514	0.445	[1,7]	0.046	0.294	0.406	0.525	0.368
	(0.007)	(0.014)	(0.014)	(0.013)	(0.013)		(0.009)	(0.018)	(0.020)	(0.020)	(0.018)
[1,4]	0.048	0.251	0.365	0.368	0.201	[1,4]	0.041	0.235	0.348	0.365	0.165
	(0.006)	(0.013)	(0.015)	(0.015)	(0.012)		(0.009)	(0.018)	(0.016)	(0.017)	(0.016)
[4,5]	0.038	0.250	0.337	0.354	0.162	[4,5]	0.061	0.268	0.339	0.328	0.089
	(0.006)	(0.014)	(0.014)	(0.014)	(0.013)		(0.009)	(0.018)	(0.018)	(0.019)	(0.013)
[5,6]	0.034	0.207	0.266	0.227	0.101	[5,6]	0.035	0.199	0.253	0.189	0.087
	(0.005)	(0.012)	(0.012)	(0.013)	(0.010)		(0.007)	(0.016)	(0.018)	(0.016)	(0.012)
[6,7]	0.038	0.234	0.323	0.310	0.161	[6,7]	0.048	0.253	0.294	0.259	0.127
	(0.006)	(0.012)	(0.013)	(0.013)	(0.010)		(0.010)	(0.016)	(0.019)	(0.017)	(0.015)
IV. Male						V. Female					
[1,7]	0.053	0.322	0.424	0.520	0.411	[1,7]	0.054	0.295	0.407	0.506	0.393
	(0.007)	(0.014)	(0.016)	(0.015)	(0.016)		(0.008)	(0.014)	(0.017)	(0.017)	(0.016)
[1,4]	0.047	0.259	0.359	0.374	0.193	[1,4]	0.051	0.238	0.354	0.350	0.184
	(0.008)	(0.014)	(0.015)	(0.016)	(0.014)		(0.008)	(0.013)	(0.015)	(0.017)	(0.015)
[4,5]	0.052	0.249	0.383	0.359	0.116	[4,5]	0.045	0.237	0.339	0.326	0.115
	(0.007)	(0.015)	(0.016)	(0.017)	(0.011)		(0.007)	(0.015)	(0.015)	(0.015)	(0.013)
[5,6]	0.037	0.199	0.245	0.228	0.088	[5,6]	0.031	0.211	0.252	0.207	0.103
	(0.007)	(0.015)	(0.015)	(0.016)	(0.010)		(0.006)	(0.016)	(0.015)	(0.014)	(0.012)
[6,7]	0.034	0.221	0.297	0.286	0.131	[6,7]	0.044	0.230	0.318	0.331	0.147
	(0.006)	(0.014)	(0.015)	(0.017)	(0.012)		(0.008)	(0.014)	(0.015)	(0.015)	(0.013)

Notes: See Table 4a.

Table 4c (cont.). Downward Mobility Measures: Percentile BMI

	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
VI. Urban						VII. Non-Urban					
[1,7]	0.055 (0.009)	0.299 (0.016)	0.388 (0.019)	0.533 (0.019)	0.392 (0.019)	[1,7]	0.052 (0.006)	0.320 (0.013)	0.433 (0.013)	0.508 (0.014)	0.420 (0.014)
[1,4]	0.043 (0.008)	0.228 (0.015)	0.346 (0.017)	0.360 (0.019)	0.203 (0.019)	[1,4]	0.053 (0.006)	0.254 (0.012)	0.365 (0.013)	0.366 (0.013)	0.181 (0.013)
[4,5]	0.045 (0.009)	0.233 (0.019)	0.347 (0.019)	0.365 (0.021)	0.098 (0.015)	[4,5]	0.052 (0.007)	0.252 (0.014)	0.367 (0.015)	0.340 (0.014)	0.130 (0.011)
[5,6]	0.036 (0.007)	0.187 (0.019)	0.246 (0.020)	0.236 (0.017)	0.074 (0.013)	[5,6]	0.040 (0.006)	0.211 (0.013)	0.251 (0.013)	0.208 (0.013)	0.102 (0.010)
[6,7]	0.041 (0.007)	0.226 (0.016)	0.293 (0.016)	0.319 (0.019)	0.124 (0.014)	[6,7]	0.031 (0.006)	0.225 (0.012)	0.328 (0.013)	0.295 (0.014)	0.152 (0.011)
VIII. Less Than College						IX. College					
[1,7]	0.060 (0.006)	0.313 (0.012)	0.422 (0.013)	0.521 (0.013)	0.393 (0.013)	[1,7]	0.043 (0.010)	0.293 (0.020)	0.423 (0.023)	0.493 (0.023)	0.422 (0.021)
[1,4]	0.049 (0.006)	0.246 (0.011)	0.373 (0.013)	0.370 (0.014)	0.164 (0.012)	[1,4]	0.043 (0.011)	0.252 (0.017)	0.333 (0.021)	0.359 (0.022)	0.215 (0.019)
[4,5]	0.056 (0.006)	0.253 (0.014)	0.355 (0.013)	0.352 (0.013)	0.099 (0.010)	[4,5]	0.041 (0.010)	0.226 (0.020)	0.356 (0.021)	0.342 (0.019)	0.163 (0.017)
[5,6]	0.034 (0.006)	0.197 (0.013)	0.242 (0.011)	0.214 (0.011)	0.101 (0.009)	[5,6]	0.026 (0.007)	0.222 (0.021)	0.285 (0.019)	0.234 (0.018)	0.090 (0.013)
[6,7]	0.038 (0.005)	0.247 (0.011)	0.304 (0.012)	0.300 (0.013)	0.144 (0.011)	[6,7]	0.045 (0.010)	0.228 (0.019)	0.309 (0.020)	0.331 (0.021)	0.153 (0.015)
X. Low SES						XI. High SES					
[1,7]	0.056 (0.011)	0.307 (0.018)	0.414 (0.020)	0.535 (0.019)	0.379 (0.020)	[1,7]	0.053 (0.007)	0.307 (0.014)	0.425 (0.015)	0.503 (0.014)	0.426 (0.013)
[1,4]	0.043 (0.011)	0.239 (0.019)	0.374 (0.020)	0.392 (0.019)	0.160 (0.015)	[1,4]	0.049 (0.006)	0.252 (0.011)	0.356 (0.013)	0.347 (0.014)	0.198 (0.012)
[4,5]	0.041 (0.008)	0.283 (0.022)	0.355 (0.019)	0.343 (0.019)	0.098 (0.016)	[4,5]	0.049 (0.006)	0.243 (0.014)	0.336 (0.013)	0.359 (0.013)	0.131 (0.011)
[5,6]	0.030 (0.008)	0.202 (0.018)	0.226 (0.018)	0.215 (0.017)	0.102 (0.015)	[5,6]	0.034 (0.005)	0.214 (0.012)	0.266 (0.013)	0.229 (0.014)	0.100 (0.009)
[6,7]	0.049 (0.009)	0.256 (0.019)	0.312 (0.017)	0.277 (0.019)	0.147 (0.015)	[6,7]	0.045 (0.006)	0.219 (0.011)	0.319 (0.012)	0.307 (0.014)	0.152 (0.010)

Table 5. Dynamic Panel Data Estimates: Weight Z-Scores.

	Full Sample			Race						Gender					
				White			Non-White			Male			Female		
Lag Weight	0.931*	0.932*	0.775*	0.932*	0.932*	0.686*	0.929*	0.931*	0.895*	0.948*	0.951*	0.276*	0.914*	0.910*	1.732*
	(0.003)	(0.003)	(0.067)	(0.004)	(0.004)	(0.080)	(0.004)	(0.004)	(0.116)	(0.004)	(0.004)	(0.056)	(0.004)	(0.004)	(0.219)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	27470	27470	27470	16900	16900	16900	10570	10570	10570	13880	13880	13880	13580	13580	13580
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.186	p = 0.050	p = 0.000	p = 0.113	p = 0.007	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	88146.9	84006.9	269.0	49635.2	48281.7	172.4	37871.6	35837.8	101.4	37300.4	36297.2	195.2	55116.6	51193.2	80.0

	Urban Status						Mother's Education						SES Status					
	Urban			Non-Urban			Less Than College			College			Low SES			High SES		
Lag Weight	0.929*	0.930*	0.896*	0.933*	0.932*	0.708*	0.931*	0.932*	0.743*	0.930*	0.930*	0.887*	0.929*	0.934*	0.807*	0.931*	0.931*	0.778*
	(0.004)	(0.005)	(0.116)	(0.003)	(0.004)	(0.082)	(0.003)	(0.003)	(0.077)	(0.006)	(0.006)	(0.146)	(0.005)	(0.005)	(0.135)	(0.003)	(0.003)	(0.077)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	10010	10010	10010	17460	17460	17460	20250	20250	20250	7210	7210	7210	8340	8340	8340	19120	19120	19120
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.060	p = 0.006	p = 0.000	p = 0.003	p = 0.000	p = 0.000	p = 0.002	p = 0.000	p = 0.000	p = 0.005	p = 0.001	p = 0.000	p = 0.102	p = 0.036	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	33299.8	31697.0	103.1	54867.6	52628.1	167.7	65410.2	62000.1	186.1	23916.2	22706.4	78.0	28392.3	26903.2	65.3	59580.3	57058.5	212.0

Notes: ‡ p<0.10, † p<0.05, * p<0.01. Robust standard errors in parentheses. Estimation by GMM. Excluded instrument is the dependent variable twice-lagged. Sample sizes rounded to the nearest 10 per NCES restricted data regulations. Sample includes data from fall kindergarten, spring first, spring third, spring fifth grades, and spring eighth grade. See text for the list of covariates and further details.

Table 6. Dynamic Panel Data Estimates: Height Z-Scores.

	Full Sample			Race						Gender					
				White			Non-White			Male			Female		
Lag Height	0.937*	0.936*	0.603*	0.938*	0.941*	0.553*	0.932*	0.932*	0.676*	0.951*	0.954*	0.460*	0.922*	0.918*	0.739*
	(0.004)	(0.004)	(0.048)	(0.004)	(0.004)	(0.057)	(0.007)	(0.007)	(0.082)	(0.004)	(0.005)	(0.055)	(0.006)	(0.006)	(0.079)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	27470	27470	27470	16900	16900	16900	10570	10570	10570	13880	13880	13880	13580	13580	13580
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	68631.4	64548.2	673.1	42314.9	40485.2	388.5	26601.1	24081.3	284.7	34323.0	31415.4	326.6	34269.4	32561.6	339.9

	Urban Status						Mother's Education						SES Status					
	Urban			Non-Urban			Less Than College			College			Low SES			High SES		
Lag Height	0.923*	0.922*	0.646*	0.945*	0.945*	0.580*	0.936*	0.936*	0.659*	0.939*	0.939*	0.453*	0.932*	0.933*	0.705*	0.938*	0.939*	0.560*
	(0.006)	(0.007)	(0.073)	(0.005)	(0.005)	(0.064)	(0.004)	(0.004)	(0.059)	(0.007)	(0.007)	(0.081)	(0.007)	(0.008)	(0.096)	(0.004)	(0.004)	(0.054)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	10010	10010	10010	17460	17460	17460	20250	20250	20250	7210	7210	7210	8340	8340	8340	19120	19120	19120
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	20304.1	19094.2	270.5	50866.0	47176.7	405.4	54613.3	51233.9	498.4	14521.0	13396.4	166.2	21762.4	20541.3	211.9	46682.7	44002.2	464.8

Notes: ‡ p<0.10, † p<0.05, * p<0.01. See Table 5 and text for further details.

Table 7. Dynamic Panel Data Estimates: Body Mass Index Z-Scores.

	Full Sample			Race						Gender					
				White			Non-White			Male			Female		
Lag BMI	0.912*	0.911*	0.217*	0.915*	0.912*	0.194*	0.904*	0.910*	0.255*	0.915*	0.919*	0.179*	0.909*	0.903*	0.275*
	(0.004)	(0.005)	(0.015)	(0.006)	(0.006)	(0.018)	(0.007)	(0.007)	(0.027)	(0.007)	(0.007)	(0.018)	(0.006)	(0.006)	(0.026)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	27470	27470	27470	16900	16900	16900	10570	10570	10570	13880	13880	13880	13580	13580	13580
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	8637.8	8518.0	820.8	4744.4	4885.9	535.8	3823.7	3657.3	293.8	3555.1	3516.1	451.8	6391.0	6229.0	420.2

	Urban Status						Mother's Education						SES Status					
	Urban			Non-Urban			Less Than College			College			Low SES			High SES		
Lag BMI	0.912*	0.909*	0.254*	0.912*	0.911*	0.200*	0.906*	0.908*	0.216*	0.921*	0.920*	0.227*	0.905*	0.912*	0.222*	0.912*	0.910*	0.222*
	(0.007)	(0.007)	(0.027)	(0.006)	(0.006)	(0.018)	(0.005)	(0.005)	(0.017)	(0.009)	(0.009)	(0.030)	(0.008)	(0.008)	(0.028)	(0.006)	(0.006)	(0.018)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	10010	10010	10010	17460	17460	17460	20250	20250	20250	7210	7210	7210	8340	8340	8340	19120	19120	19120
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	3452.7	3187.6	278.1	5265.0	5388.1	545.0	6257.6	6090.8	575.5	2448.2	2562.1	254.0	3340.8	3264.5	251.2	5367.1	5346.3	579.1

Notes: ‡ p<0.10, † p<0.05, * p<0.01. See Table 5 and text for further details.

Table 8a. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \geq 85^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.840	0.823	0.861	0.846	0.833	0.840	0.840	0.870	0.748	0.880	0.820
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.753	0.681	0.846	0.765	0.739	0.776	0.740	0.800	0.609	0.868	0.695
$\alpha \sim f(\alpha)$	0.576	0.555	0.604	0.581	0.570	0.586	0.570	0.588	0.540	0.609	0.559
$\alpha \sim f_i(\alpha)$		0.552	0.608	0.597	0.555	0.565	0.584	0.607	0.484	0.637	0.547
$\alpha \sim f_{-i}(\alpha)$		0.562	0.602	0.567	0.586	0.599	0.551	0.537	0.561	0.597	0.593
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.727	0.642	0.837	0.800	0.645	0.714	0.734	0.829	0.418	0.894	0.643
$W \sim f(W)$	0.703	0.649	0.775	0.710	0.696	0.729	0.689	0.736	0.604	0.786	0.662
$W \sim f_i(W)$		0.632	0.789	0.778	0.622	0.672	0.724	0.802	0.394	0.870	0.614
$W \sim f_{-i}(W)$		0.676	0.765	0.640	0.767	0.759	0.631	0.550	0.678	0.748	0.769
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.591	0.563	0.628	0.616	0.563	0.582	0.596	0.622	0.497	0.652	0.561
$\eta \sim f_i(\eta)$		0.566	0.620	0.608	0.569	0.580	0.596	0.617	0.500	0.642	0.562
$\eta \sim f_{-i}(\eta)$		0.558	0.632	0.625	0.557	0.582	0.593	0.635	0.496	0.653	0.557
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.844	0.834	0.858	0.850	0.838	0.837	0.848	0.867	0.777	0.867	0.833
$X \sim f(X)$	0.849	0.841	0.860	0.855	0.843	0.841	0.854	0.871	0.783	0.870	0.839
$X \sim f_i(X)$		0.834	0.868	0.854	0.844	0.844	0.852	0.873	0.771	0.877	0.834
$X \sim f_{-i}(X)$		0.852	0.856	0.856	0.843	0.839	0.857	0.864	0.788	0.866	0.852
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.846	0.830	0.868	0.854	0.838	0.842	0.849	0.873	0.766	0.880	0.830
$\varepsilon \sim f_i(\varepsilon)$		0.831	0.866	0.852	0.841	0.844	0.848	0.873	0.766	0.881	0.829
$\varepsilon \sim f_{-i}(\varepsilon)$		0.829	0.868	0.857	0.834	0.840	0.852	0.873	0.765	0.880	0.832
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.843	0.835	0.854	0.851	0.835	0.833	0.849	0.866	0.775	0.863	0.833
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.829	0.862	0.848	0.840	0.839	0.846	0.869	0.761	0.873	0.827
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.845	0.849	0.854	0.831	0.830	0.855	0.859	0.779	0.860	0.848

Notes: Benchmark case denotes the observed probability in the sample. Simulations obtained after estimating the dynamic model $y_{it} = \alpha_i + \gamma y_{it-1} + X_{it}\beta + \varepsilon_{it}$, where $\alpha_i = w_i\delta + \eta_i$. $f(\cdot)$ denotes the empirical distribution of the argument. Sample includes data from fall kindergarten, spring first, spring third, spring fifth grades, and spring eighth grade. See text for the list of covariates and further details.

Table 8b. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 95^{\text{th}} \text{ percentile} \mid y_{it} \geq 95^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.762	0.732	0.795	0.807	0.710	0.791	0.746	0.790	0.646	0.799	0.740
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.134	0.093	0.180	0.171	0.091	0.150	0.125	0.151	0.067	0.183	0.105
$\alpha \sim f(\alpha)$	0.396	0.376	0.418	0.404	0.387	0.408	0.390	0.370	0.403	0.420	0.382
$\alpha \sim f_i(\alpha)$		0.368	0.431	0.434	0.356	0.386	0.403	0.300	0.428	0.461	0.364
$\alpha \sim f_{-i}(\alpha)$		0.390	0.411	0.377	0.418	0.420	0.371	0.398	0.337	0.405	0.425
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.246	0.194	0.302	0.305	0.175	0.196	0.273	0.079	0.286	0.348	0.185
$W \sim f(W)$	0.196	0.152	0.245	0.221	0.167	0.218	0.185	0.135	0.212	0.253	0.163
$W \sim f_i(W)$		0.140	0.268	0.265	0.121	0.168	0.209	0.057	0.248	0.330	0.138
$W \sim f_{-i}(W)$		0.172	0.231	0.177	0.211	0.244	0.142	0.161	0.109	0.222	0.220
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.418	0.397	0.441	0.443	0.388	0.406	0.425	0.332	0.439	0.464	0.391
$\eta \sim f_i(\eta)$		0.395	0.443	0.444	0.384	0.408	0.426	0.318	0.441	0.467	0.388
$\eta \sim f_{-i}(\eta)$		0.405	0.439	0.442	0.397	0.404	0.427	0.341	0.435	0.465	0.398
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.780	0.774	0.786	0.809	0.746	0.791	0.773	0.691	0.801	0.796	0.770
$X \sim f(X)$	0.784	0.777	0.792	0.811	0.753	0.792	0.780	0.695	0.806	0.800	0.775
$X \sim f_i(X)$		0.768	0.806	0.811	0.753	0.797	0.778	0.682	0.810	0.816	0.769
$X \sim f_{-i}(X)$		0.792	0.784	0.813	0.751	0.788	0.786	0.700	0.795	0.793	0.791
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.786	0.763	0.811	0.813	0.754	0.806	0.775	0.678	0.812	0.820	0.766
$\varepsilon \sim f_i(\varepsilon)$		0.765	0.809	0.811	0.759	0.811	0.773	0.679	0.812	0.822	0.766
$\varepsilon \sim f_{-i}(\varepsilon)$		0.762	0.812	0.817	0.749	0.806	0.778	0.679	0.812	0.820	0.769
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.779	0.769	0.791	0.806	0.747	0.785	0.776	0.685	0.802	0.797	0.768
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.762	0.804	0.803	0.755	0.794	0.772	0.669	0.808	0.816	0.760
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.784	0.785	0.811	0.742	0.780	0.786	0.691	0.792	0.791	0.789

Notes: See Table 8a and text for further details.

Table 8c. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 50^{\text{th}} \text{ percentile} \mid y_{it} \geq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.906	0.896	0.920	0.894	0.918	0.902	0.908	0.915	0.879	0.916	0.901
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$\alpha \sim f(\alpha)$	0.841	0.830	0.857	0.841	0.840	0.844	0.838	0.828	0.845	0.854	0.834
$\alpha \sim f_i(\alpha)$		0.833	0.854	0.840	0.842	0.831	0.847	0.807	0.853	0.858	0.833
$\alpha \sim f_{-i}(\alpha)$		0.828	0.860	0.845	0.837	0.852	0.826	0.836	0.826	0.853	0.839
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	1.000	1.000	1.000	1.000	1.000	0.999	1.000	0.999	1.000	1.000	1.000
$W \sim f(W)$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$W \sim f_i(W)$		1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000	1.000
$W \sim f_{-i}(W)$		0.999	1.000	1.000	1.000	1.000	1.000	1.000	0.999	1.000	1.000
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.843	0.829	0.865	0.857	0.828	0.835	0.847	0.794	0.861	0.875	0.829
$\eta \sim f_i(\eta)$		0.835	0.857	0.842	0.844	0.835	0.846	0.811	0.857	0.862	0.834
$\eta \sim f_{-i}(\eta)$		0.819	0.870	0.872	0.812	0.834	0.847	0.787	0.873	0.880	0.815
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.905	0.896	0.917	0.901	0.909	0.898	0.908	0.880	0.914	0.912	0.901
$X \sim f(X)$	0.907	0.900	0.918	0.902	0.913	0.903	0.910	0.886	0.915	0.914	0.904
$X \sim f_i(X)$		0.895	0.925	0.902	0.913	0.906	0.908	0.879	0.917	0.921	0.900
$X \sim f_{-i}(X)$		0.908	0.914	0.902	0.912	0.901	0.912	0.888	0.909	0.911	0.913
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.902	0.891	0.919	0.895	0.908	0.899	0.903	0.872	0.912	0.916	0.895
$\varepsilon \sim f_i(\varepsilon)$		0.891	0.918	0.893	0.910	0.901	0.902	0.873	0.912	0.917	0.895
$\varepsilon \sim f_{-i}(\varepsilon)$		0.890	0.919	0.897	0.906	0.898	0.905	0.873	0.913	0.915	0.896
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.902	0.896	0.911	0.896	0.907	0.896	0.905	0.880	0.910	0.909	0.899
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.891	0.918	0.894	0.910	0.902	0.902	0.872	0.912	0.917	0.894
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.903	0.908	0.899	0.905	0.893	0.909	0.882	0.904	0.905	0.909

Notes: See Table 8a and text for further details.

Table 8d. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \leq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.118	0.121	0.113	0.132	0.104	0.108	0.124	0.131	0.079	0.145	0.106
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.213	0.209	0.220	0.213	0.214	0.218	0.210	0.209	0.215	0.224	0.208
$\alpha \sim f_i(\alpha)$		0.198	0.238	0.244	0.182	0.205	0.218	0.146	0.238	0.264	0.192
$\alpha \sim f_{-i}(\alpha)$		0.226	0.210	0.181	0.245	0.226	0.198	0.232	0.151	0.206	0.247
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.006	0.005	0.009	0.007	0.005	0.002	0.009	0.001	0.008	0.010	0.005
$W \sim f(W)$	0.006	0.006	0.008	0.006	0.006	0.007	0.006	0.005	0.007	0.008	0.006
$W \sim f_i(W)$		0.005	0.008	0.008	0.005	0.002	0.009	0.002	0.008	0.012	0.005
$W \sim f_{-i}(W)$		0.006	0.007	0.005	0.008	0.010	0.002	0.007	0.002	0.007	0.008
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.209	0.204	0.216	0.225	0.193	0.198	0.215	0.166	0.223	0.240	0.195
$\eta \sim f_i(\eta)$		0.197	0.228	0.240	0.176	0.201	0.214	0.145	0.231	0.256	0.188
$\eta \sim f_{-i}(\eta)$		0.216	0.209	0.211	0.210	0.197	0.218	0.173	0.203	0.235	0.211
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.116	0.123	0.105	0.137	0.096	0.100	0.126	0.085	0.127	0.134	0.109
$X \sim f(X)$	0.120	0.127	0.109	0.140	0.101	0.104	0.130	0.087	0.132	0.140	0.112
$X \sim f_i(X)$		0.123	0.115	0.140	0.101	0.106	0.128	0.083	0.134	0.148	0.109
$X \sim f_{-i}(X)$		0.135	0.106	0.141	0.101	0.103	0.133	0.088	0.125	0.136	0.119
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.121	0.125	0.116	0.140	0.103	0.109	0.129	0.080	0.135	0.149	0.109
$\varepsilon \sim f_i(\varepsilon)$		0.126	0.115	0.139	0.105	0.110	0.128	0.079	0.136	0.151	0.109
$\varepsilon \sim f_{-i}(\varepsilon)$		0.124	0.116	0.143	0.101	0.108	0.131	0.080	0.135	0.149	0.111
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.124	0.131	0.112	0.143	0.105	0.108	0.133	0.088	0.136	0.143	0.115
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.127	0.117	0.140	0.107	0.111	0.130	0.082	0.138	0.153	0.111
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.138	0.109	0.145	0.103	0.106	0.138	0.090	0.129	0.139	0.125

Notes: See Table 8a and text for further details.

Table 9a. Dynamic Simulations: Height Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \geq 85^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.606	0.635	0.559	0.665	0.545	0.592	0.614	0.587	0.653	0.515	0.642
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.235	0.243	0.221	0.236	0.234	0.229	0.238	0.228	0.252	0.222	0.240
$\alpha \sim f_i(\alpha)$		0.248	0.216	0.260	0.209	0.221	0.243	0.228	0.251	0.217	0.243
$\alpha \sim f_{-i}(\alpha)$		0.237	0.223	0.210	0.259	0.236	0.228	0.228	0.250	0.222	0.234
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.006	0.006	0.008	0.010	0.002	0.008	0.005	0.004	0.012	0.002	0.008
$W \sim f(W)$	0.003	0.004	0.002	0.004	0.003	0.004	0.003	0.002	0.005	0.002	0.004
$W \sim f_i(W)$		0.003	0.004	0.006	0.002	0.003	0.003	0.002	0.007	0.002	0.004
$W \sim f_{-i}(W)$		0.007	0.001	0.002	0.004	0.005	0.002	0.003	0.006	0.002	0.004
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.256	0.265	0.241	0.281	0.230	0.246	0.261	0.247	0.279	0.231	0.266
$\eta \sim f_i(\eta)$		0.263	0.241	0.286	0.224	0.245	0.261	0.250	0.270	0.237	0.263
$\eta \sim f_{-i}(\eta)$		0.267	0.240	0.276	0.234	0.245	0.260	0.234	0.283	0.225	0.271
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.669	0.662	0.680	0.702	0.635	0.673	0.667	0.667	0.673	0.627	0.686
$X \sim f(X)$	0.663	0.655	0.675	0.695	0.629	0.664	0.662	0.664	0.660	0.626	0.677
$X \sim f_i(X)$		0.669	0.655	0.694	0.630	0.657	0.665	0.655	0.686	0.611	0.686
$X \sim f_{-i}(X)$		0.633	0.688	0.697	0.627	0.668	0.656	0.688	0.650	0.634	0.657
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.635	0.645	0.621	0.665	0.604	0.627	0.640	0.627	0.656	0.581	0.657
$\varepsilon \sim f_i(\varepsilon)$		0.667	0.587	0.680	0.590	0.616	0.645	0.622	0.670	0.562	0.667
$\varepsilon \sim f_{-i}(\varepsilon)$		0.610	0.641	0.650	0.620	0.631	0.632	0.644	0.648	0.590	0.635
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.635	0.629	0.646	0.666	0.603	0.636	0.635	0.638	0.630	0.603	0.648
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.663	0.595	0.680	0.589	0.621	0.644	0.624	0.668	0.569	0.666
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.572	0.679	0.653	0.616	0.643	0.620	0.675	0.616	0.618	0.608

Notes: Benchmark case denotes the observed probability in the sample. Simulations obtained after estimating the dynamic model $y_{it} = \alpha_i + \gamma y_{it-1} + X_{it}\beta + \varepsilon_{it}$, where $\alpha_i = w_i\delta + \eta_i$. $f(\cdot)$ denotes the empirical distribution of the argument. Sample includes data from fall kindergarten, spring first, spring third, spring fifth grades, and spring eighth grade. See text for the list of covariates and further details.

Table 9b. Dynamic Simulations: Height Z-Scores, $\Pr(y_{it} \geq 95^{\text{th}} \text{ percentile} \mid y_{it} \geq 95^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.467	0.481	0.446	0.550	0.377	0.448	0.476	0.453	0.502	0.414	0.489
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.092	0.097	0.085	0.094	0.090	0.092	0.092	0.103	0.088	0.083	0.096
$\alpha \sim f_i(\alpha)$		0.097	0.086	0.107	0.076	0.087	0.095	0.103	0.087	0.082	0.097
$\alpha \sim f_{-i}(\alpha)$		0.096	0.081	0.079	0.102	0.095	0.087	0.104	0.087	0.084	0.091
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f(W)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f_i(W)$		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f_{-i}(W)$		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.108	0.111	0.103	0.122	0.092	0.107	0.108	0.121	0.102	0.094	0.113
$\eta \sim f_i(\eta)$		0.110	0.105	0.127	0.090	0.108	0.108	0.112	0.105	0.098	0.111
$\eta \sim f_{-i}(\eta)$		0.116	0.099	0.120	0.093	0.107	0.107	0.122	0.095	0.093	0.118
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.523	0.498	0.562	0.572	0.469	0.493	0.536	0.498	0.533	0.517	0.525
$X \sim f(X)$	0.523	0.495	0.568	0.569	0.473	0.499	0.534	0.500	0.532	0.520	0.524
$X \sim f_i(X)$		0.509	0.540	0.566	0.475	0.492	0.539	0.530	0.522	0.497	0.533
$X \sim f_{-i}(X)$		0.470	0.585	0.570	0.472	0.503	0.526	0.488	0.562	0.531	0.502
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.506	0.496	0.522	0.545	0.463	0.480	0.518	0.505	0.506	0.485	0.514
$\varepsilon \sim f_i(\varepsilon)$		0.517	0.487	0.559	0.449	0.470	0.523	0.523	0.499	0.466	0.524
$\varepsilon \sim f_{-i}(\varepsilon)$		0.461	0.543	0.530	0.477	0.484	0.508	0.498	0.521	0.496	0.493
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.509	0.481	0.552	0.546	0.468	0.489	0.518	0.481	0.519	0.509	0.509
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.517	0.494	0.558	0.457	0.476	0.528	0.523	0.506	0.470	0.528
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.425	0.587	0.533	0.479	0.497	0.502	0.467	0.561	0.525	0.468

Notes: See Table 9a and text for further details.

Table 9c. Dynamic Simulations: Height Z-Scores, $\Pr(y_{it} \geq 50^{\text{th}} \text{ percentile} \mid y_{it} \geq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.786	0.820	0.731	0.832	0.741	0.769	0.796	0.777	0.809	0.736	0.807
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.982	0.993	0.962	0.979	0.984	0.975	0.986	0.976	0.997	0.967	0.988
$\alpha \sim f(\alpha)$	0.622	0.634	0.602	0.621	0.622	0.616	0.625	0.643	0.613	0.604	0.629
$\alpha \sim f_i(\alpha)$		0.644	0.586	0.651	0.592	0.604	0.631	0.661	0.607	0.582	0.639
$\alpha \sim f_{-i}(\alpha)$		0.618	0.611	0.591	0.651	0.622	0.613	0.637	0.631	0.612	0.607
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.887	0.956	0.773	0.929	0.845	0.837	0.914	0.945	0.864	0.796	0.924
$W \sim f(W)$	0.881	0.906	0.840	0.879	0.883	0.868	0.888	0.919	0.866	0.844	0.896
$W \sim f_i(W)$		0.949	0.754	0.930	0.833	0.835	0.906	0.941	0.854	0.781	0.917
$W \sim f_{-i}(W)$		0.839	0.893	0.828	0.933	0.888	0.858	0.911	0.900	0.873	0.850
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.633	0.653	0.602	0.663	0.604	0.617	0.643	0.666	0.621	0.598	0.648
$\eta \sim f_i(\eta)$		0.653	0.600	0.661	0.602	0.614	0.644	0.673	0.618	0.593	0.650
$\eta \sim f_{-i}(\eta)$		0.651	0.603	0.663	0.605	0.619	0.638	0.663	0.628	0.596	0.645
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.837	0.844	0.826	0.863	0.812	0.834	0.839	0.835	0.838	0.826	0.842
$X \sim f(X)$	0.833	0.839	0.824	0.859	0.807	0.828	0.836	0.830	0.834	0.820	0.839
$X \sim f_i(X)$		0.849	0.807	0.858	0.809	0.823	0.839	0.848	0.828	0.806	0.845
$X \sim f_{-i}(X)$		0.824	0.834	0.860	0.806	0.831	0.832	0.824	0.853	0.826	0.825
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.810	0.827	0.784	0.836	0.784	0.798	0.817	0.821	0.806	0.784	0.821
$\varepsilon \sim f_i(\varepsilon)$		0.843	0.754	0.848	0.770	0.790	0.821	0.833	0.801	0.767	0.828
$\varepsilon \sim f_{-i}(\varepsilon)$		0.800	0.802	0.824	0.797	0.802	0.810	0.817	0.818	0.791	0.804
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.806	0.812	0.797	0.832	0.780	0.799	0.810	0.799	0.809	0.795	0.811
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.838	0.753	0.844	0.768	0.787	0.817	0.830	0.798	0.766	0.824
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.770	0.824	0.819	0.793	0.806	0.799	0.789	0.837	0.807	0.781

Notes: See Table 9a and text for further details.

Table 9d. Dynamic Simulations: Height Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \leq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.030	0.036	0.019	0.032	0.027	0.025	0.032	0.030	0.029	0.026	0.032
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.144	0.151	0.134	0.144	0.145	0.141	0.146	0.158	0.140	0.136	0.149
$\alpha \sim f_i(\alpha)$		0.153	0.135	0.163	0.126	0.134	0.151	0.157	0.141	0.134	0.150
$\alpha \sim f_{-i}(\alpha)$		0.151	0.135	0.125	0.164	0.145	0.140	0.160	0.138	0.135	0.147
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f(W)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f_i(W)$		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f_{-i}(W)$		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.133	0.145	0.115	0.149	0.117	0.125	0.138	0.155	0.126	0.114	0.142
$\eta \sim f_i(\eta)$		0.143	0.119	0.153	0.115	0.126	0.138	0.144	0.130	0.119	0.139
$\eta \sim f_{-i}(\eta)$		0.149	0.114	0.145	0.120	0.125	0.139	0.159	0.118	0.112	0.149
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.019	0.020	0.017	0.019	0.019	0.021	0.018	0.014	0.020	0.020	0.018
$X \sim f(X)$	0.018	0.019	0.016	0.017	0.018	0.019	0.017	0.014	0.019	0.019	0.017
$X \sim f_i(X)$		0.020	0.014	0.017	0.018	0.018	0.017	0.015	0.018	0.018	0.018
$X \sim f_{-i}(X)$		0.017	0.017	0.017	0.018	0.019	0.017	0.013	0.021	0.020	0.015
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.021	0.024	0.016	0.022	0.020	0.021	0.021	0.021	0.021	0.021	0.021
$\varepsilon \sim f_i(\varepsilon)$		0.026	0.014	0.022	0.020	0.020	0.021	0.023	0.020	0.019	0.022
$\varepsilon \sim f_{-i}(\varepsilon)$		0.021	0.018	0.021	0.020	0.021	0.020	0.021	0.023	0.021	0.019
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.022	0.024	0.019	0.023	0.021	0.023	0.022	0.019	0.023	0.023	0.022
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.027	0.015	0.023	0.021	0.022	0.022	0.024	0.021	0.020	0.023
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.019	0.022	0.023	0.021	0.023	0.021	0.018	0.028	0.024	0.018

Notes: See Table 9a and text for further details.

Table 10a. Dynamic Simulations: BMI Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \geq 85^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.746	0.703	0.800	0.736	0.757	0.758	0.739	0.779	0.637	0.813	0.710
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.001	0.000	0.000	0.001	0.000	0.001	0.000	0.002	0.000	0.001
$\alpha \sim f(\alpha)$	0.347	0.348	0.345	0.346	0.347	0.347	0.347	0.357	0.344	0.341	0.350
$\alpha \sim f_i(\alpha)$		0.309	0.407	0.357	0.337	0.344	0.348	0.265	0.376	0.420	0.316
$\alpha \sim f_{-i}(\alpha)$		0.410	0.307	0.334	0.360	0.348	0.345	0.392	0.250	0.306	0.430
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.070	0.011	0.145	0.076	0.065	0.079	0.066	0.004	0.090	0.147	0.030
$W \sim f(W)$	0.055	0.056	0.055	0.054	0.057	0.054	0.056	0.071	0.051	0.049	0.059
$W \sim f_i(W)$		0.015	0.118	0.065	0.044	0.059	0.052	0.006	0.067	0.108	0.028
$W \sim f_{-i}(W)$		0.121	0.015	0.041	0.069	0.050	0.062	0.093	0.004	0.023	0.130
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.368	0.333	0.412	0.376	0.359	0.370	0.366	0.299	0.389	0.413	0.344
$\eta \sim f_i(\eta)$		0.324	0.421	0.379	0.356	0.373	0.365	0.277	0.394	0.433	0.333
$\eta \sim f_{-i}(\eta)$		0.347	0.406	0.374	0.363	0.370	0.369	0.306	0.378	0.406	0.364
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.797	0.761	0.842	0.793	0.802	0.798	0.797	0.708	0.824	0.845	0.772
$X \sim f(X)$	0.795	0.759	0.840	0.791	0.800	0.798	0.793	0.707	0.822	0.844	0.769
$X \sim f_i(X)$		0.761	0.837	0.789	0.802	0.798	0.793	0.723	0.818	0.837	0.773
$X \sim f_{-i}(X)$		0.756	0.841	0.792	0.798	0.798	0.793	0.701	0.831	0.847	0.760
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.766	0.733	0.807	0.764	0.768	0.768	0.764	0.688	0.789	0.807	0.744
$\varepsilon \sim f_i(\varepsilon)$		0.733	0.806	0.752	0.780	0.770	0.762	0.670	0.793	0.816	0.739
$\varepsilon \sim f_{-i}(\varepsilon)$		0.732	0.807	0.775	0.754	0.767	0.767	0.696	0.775	0.802	0.755
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.765	0.730	0.808	0.763	0.766	0.768	0.762	0.672	0.792	0.813	0.739
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.732	0.806	0.750	0.781	0.771	0.761	0.670	0.793	0.817	0.737
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.726	0.811	0.777	0.752	0.768	0.764	0.674	0.789	0.812	0.741

Notes: Benchmark case denotes the observed probability in the sample. Simulations obtained after estimating the dynamic model $y_{it} = \alpha_i + \gamma y_{it-1} + X_{it}\beta + \varepsilon_{it}$, where $\alpha_i = w_i\delta + \eta_i$. $f(\cdot)$ denotes the empirical distribution of the argument. Sample includes data from fall kindergarten, spring first, spring third, spring fifth grades, and spring eighth grade. See text for the list of covariates and further details.

Table 10b. Dynamic Simulations: BMI Z-Scores, $\Pr(y_{it} \geq 95^{\text{th}} \text{ percentile} \mid y_{it} \geq 95^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.715	0.664	0.769	0.724	0.703	0.738	0.702	0.757	0.538	0.783	0.672
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.179	0.180	0.178	0.178	0.180	0.177	0.179	0.187	0.177	0.175	0.181
$\alpha \sim f_i(\alpha)$		0.147	0.228	0.194	0.161	0.181	0.176	0.117	0.199	0.233	0.153
$\alpha \sim f_{-i}(\alpha)$		0.231	0.144	0.158	0.196	0.176	0.179	0.211	0.109	0.149	0.242
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f(W)$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f_i(W)$		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$W \sim f_{-i}(W)$		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.195	0.171	0.221	0.199	0.190	0.195	0.196	0.137	0.209	0.226	0.176
$\eta \sim f_i(\eta)$		0.162	0.238	0.207	0.182	0.198	0.193	0.124	0.216	0.244	0.168
$\eta \sim f_{-i}(\eta)$		0.184	0.212	0.192	0.197	0.194	0.198	0.142	0.190	0.217	0.193
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.792	0.757	0.830	0.804	0.778	0.810	0.782	0.629	0.832	0.845	0.759
$X \sim f(X)$	0.792	0.758	0.827	0.802	0.778	0.808	0.782	0.628	0.831	0.841	0.761
$X \sim f_i(X)$		0.760	0.824	0.801	0.781	0.808	0.783	0.648	0.826	0.830	0.766
$X \sim f_{-i}(X)$		0.754	0.830	0.805	0.776	0.809	0.782	0.622	0.845	0.846	0.749
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.734	0.699	0.771	0.739	0.728	0.748	0.726	0.597	0.767	0.776	0.708
$\varepsilon \sim f_i(\varepsilon)$		0.698	0.770	0.723	0.746	0.752	0.724	0.575	0.774	0.788	0.700
$\varepsilon \sim f_{-i}(\varepsilon)$		0.698	0.771	0.755	0.710	0.747	0.729	0.606	0.747	0.770	0.721
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.735	0.699	0.773	0.742	0.726	0.749	0.727	0.583	0.771	0.784	0.704
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.700	0.770	0.724	0.743	0.750	0.727	0.579	0.772	0.787	0.702
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.694	0.775	0.761	0.706	0.749	0.729	0.583	0.767	0.783	0.706

Notes: See Table 10a and text for further details.

Table 10c. Dynamic Simulations: BMI Z-Scores, $\Pr(y_{it} \geq 50^{\text{th}} \text{ percentile} \mid y_{it} \geq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.851	0.834	0.877	0.835	0.867	0.847	0.853	0.868	0.802	0.884	0.836
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
$\alpha \sim f(\alpha)$	0.721	0.723	0.719	0.721	0.722	0.721	0.722	0.732	0.718	0.714	0.725
$\alpha \sim f_i(\alpha)$		0.702	0.755	0.729	0.715	0.712	0.727	0.674	0.739	0.765	0.704
$\alpha \sim f_{-i}(\alpha)$		0.758	0.697	0.712	0.731	0.726	0.712	0.753	0.657	0.690	0.776
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.997	0.996	0.999	0.997	0.997	0.996	0.998	0.990	1.000	0.999	0.996
$W \sim f(W)$	0.993	0.993	0.991	0.992	0.993	0.992	0.993	0.996	0.991	0.989	0.994
$W \sim f_i(W)$		0.992	0.994	0.994	0.991	0.989	0.994	0.986	0.998	0.999	0.992
$W \sim f_{-i}(W)$		0.996	0.989	0.989	0.995	0.994	0.990	0.999	0.972	0.984	1.000
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.730	0.702	0.773	0.739	0.721	0.728	0.731	0.664	0.753	0.776	0.709
$\eta \sim f_i(\eta)$		0.709	0.762	0.733	0.727	0.724	0.734	0.676	0.749	0.772	0.709
$\eta \sim f_{-i}(\eta)$		0.692	0.780	0.746	0.715	0.730	0.727	0.660	0.766	0.776	0.710
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.874	0.854	0.904	0.870	0.878	0.874	0.873	0.832	0.888	0.907	0.858
$X \sim f(X)$	0.873	0.853	0.902	0.869	0.877	0.873	0.873	0.828	0.888	0.907	0.857
$X \sim f_i(X)$		0.855	0.900	0.868	0.878	0.873	0.873	0.841	0.885	0.902	0.860
$X \sim f_{-i}(X)$		0.851	0.904	0.870	0.876	0.873	0.872	0.824	0.896	0.910	0.850
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.848	0.829	0.877	0.844	0.852	0.847	0.848	0.804	0.863	0.881	0.833
$\varepsilon \sim f_i(\varepsilon)$		0.829	0.877	0.835	0.861	0.849	0.847	0.789	0.866	0.887	0.829
$\varepsilon \sim f_{-i}(\varepsilon)$		0.829	0.877	0.854	0.842	0.847	0.850	0.808	0.853	0.878	0.841
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.846	0.826	0.877	0.843	0.849	0.845	0.846	0.793	0.864	0.885	0.828
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.828	0.875	0.833	0.860	0.847	0.845	0.790	0.865	0.887	0.828
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.824	0.878	0.854	0.838	0.845	0.847	0.794	0.862	0.884	0.830

Notes: See Table 10a and text for further details.

Table 10d. Dynamic Simulations: BMI Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \leq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES	High SES
Benchmark	0.142	0.127	0.167	0.152	0.132	0.138	0.144	0.162	0.087	0.192	0.121
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.346	0.347	0.343	0.345	0.347	0.346	0.346	0.356	0.342	0.339	0.348
$\alpha \sim f_i(\alpha)$		0.308	0.403	0.354	0.335	0.344	0.347	0.263	0.375	0.418	0.315
$\alpha \sim f_{-i}(\alpha)$		0.410	0.304	0.333	0.359	0.348	0.342	0.390	0.249	0.304	0.428
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.044	0.020	0.086	0.051	0.036	0.032	0.050	0.005	0.058	0.094	0.023
$W \sim f(W)$	0.054	0.054	0.053	0.052	0.055	0.054	0.053	0.066	0.049	0.047	0.056
$W \sim f_i(W)$		0.014	0.114	0.063	0.042	0.061	0.049	0.005	0.065	0.105	0.026
$W \sim f_{-i}(W)$		0.118	0.014	0.040	0.067	0.051	0.058	0.087	0.003	0.021	0.126
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.335	0.311	0.378	0.345	0.326	0.328	0.339	0.270	0.360	0.392	0.312
$\eta \sim f_i(\eta)$		0.300	0.387	0.347	0.320	0.329	0.337	0.248	0.363	0.410	0.303
$\eta \sim f_{-i}(\eta)$		0.324	0.370	0.341	0.328	0.325	0.341	0.276	0.345	0.383	0.332
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.105	0.096	0.120	0.120	0.091	0.092	0.113	0.062	0.121	0.139	0.091
$X \sim f(X)$	0.107	0.098	0.121	0.121	0.092	0.095	0.113	0.062	0.123	0.142	0.092
$X \sim f_i(X)$		0.099	0.121	0.121	0.093	0.095	0.113	0.067	0.121	0.138	0.094
$X \sim f_{-i}(X)$		0.097	0.122	0.122	0.092	0.095	0.113	0.060	0.129	0.144	0.089
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.125	0.116	0.139	0.138	0.111	0.115	0.130	0.086	0.139	0.158	0.111
$\varepsilon \sim f_i(\varepsilon)$		0.116	0.139	0.131	0.117	0.116	0.129	0.079	0.142	0.163	0.109
$\varepsilon \sim f_{-i}(\varepsilon)$		0.116	0.138	0.145	0.105	0.114	0.131	0.088	0.131	0.155	0.115
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.125	0.116	0.140	0.140	0.111	0.115	0.131	0.083	0.141	0.161	0.111
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.116	0.140	0.132	0.117	0.116	0.130	0.081	0.141	0.162	0.110
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.116	0.141	0.147	0.105	0.114	0.132	0.083	0.139	0.161	0.111

Notes: See Table 10a and text for further details.

Table 11. Dynamic Panel Data Estimates: Weight Z-Scores.

	Full Sample			Race						Gender					
				White			Non-White			Male			Female		
Lag Weight	0.873*	0.870*	0.124*	0.868*	0.903*	0.105*	0.873*	0.857*	0.144*	0.888*	0.896*	0.108*	0.857*	0.850*	0.143*
	(0.010)	(0.012)	(0.013)	(0.016)	(0.021)	(0.018)	(0.013)	(0.016)	(0.018)	(0.014)	(0.019)	(0.019)	(0.014)	(0.017)	(0.018)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	10900	10900	10900	4500	4500	4500	6400	6400	6400	5450	5450	5450	5400	5400	5400
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	112.0	1398.4	1929.3	626.3	429.3	803.7	1683.9	1112.7	1253.0	321.8	778.8	972.4	889.5	640.4	965.5

	Urban Status						Mother's Education						SES Status					
	Urban			Non-Urban			Less Than College			College			Low SES			High SES		
Lag Weight	0.874*	0.869*	0.130*	0.870*	0.894*	0.121*	0.864*	0.886*	0.123*	0.875*	0.872*	0.126*	0.868*	0.887*	0.127*	0.874*	0.860*	0.128*
	(0.012)	(0.015)	(0.016)	(0.018)	(0.024)	(0.023)	(0.018)	(0.024)	(0.023)	(0.012)	(0.015)	(0.016)	(0.018)	(0.021)	(0.022)	(0.012)	(0.015)	(0.016)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7800	7800	7800	3100	3100	3100	7750	7750	7750	3150	3150	3150	4050	4050	4050	6850	6850	6850
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	1785.2	1184.3	1566.7	469.1	342.0	497.2	697.1	447.3	715.3	1455.9	978.3	1261.1	686.6	481.3	687.5	1497.8	988.9	1339.1

Notes: ‡ p<0.10, † p<0.05, * p<0.01. Robust standard errors in parentheses. Estimation by GMM. Excluded instrument is the dependent variable twice-lagged. Sample sizes rounded to the nearest 50 per NCES restricted data regulations. Sample includes data from waves 1-4 in the ECLS-B. See text for the list of covariates and further details.

Table 12. Dynamic Panel Data Estimates: Height.

	Full Sample			Race						Gender					
				White			Non-White			Male			Female		
Lag Height	0.480*	0.506*	-0.002	0.488*	0.522*	0.002	0.474*	0.493*	-0.005	0.485*	0.511*	-0.056*	0.474*	0.498*	-0.043*
	(0.004)	(0.010)	(0.007)	(0.006)	(0.016)	(0.012)	(0.005)	(0.013)	(0.009)	(0.006)	(0.014)	(0.008)	(0.006)	(0.015)	(0.008)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	10900	10900	10900	4500	4500	4500	6400	6400	6400	5450	5450	5450	5400	5400	5400
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	770.2	6940.2	10250.2	17737.1	2263.8	3947.3	27111.7	4758.6	6311.6	568.9	3435.1	8396.2	21349.5	3328.9	8158.5

	Urban Status						Mother's Education						SES Status					
	Urban			Non-Urban			Less Than College			College			Low SES			High SES		
Lag Height	0.475*	0.491*	-0.049*	0.493*	0.549*	-0.057*	0.481*	0.492*	-0.051*	0.480*	0.515*	-0.049*	0.466*	0.486*	-0.055*	0.488*	0.524*	-0.045*
	(0.005)	(0.012)	(0.007)	(0.008)	(0.021)	(0.011)	(0.007)	(0.018)	(0.010)	(0.005)	(0.012)	(0.007)	(0.007)	(0.017)	(0.009)	(0.005)	(0.013)	(0.007)
Time-Varying Covariates	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time Invariant Covariates	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	7800	7800	7800	3100	3100	3100	7750	7750	7750	3150	3150	3150	4050	4050	4050	6850	6850	6850
Underidentification	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
Endogeneity	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.006	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
First-Stage F-stat	33778.2	5408.6	12465.7	310.8	1489.6	3939.6	13369.8	1660.6	4565.1	31408.3	5230.3	11710.0	246.8	2752.0	6982.2	28553.6	4057.3	9316.1

Notes: ‡ p<0.10, † p<0.05, * p<0.01. Dependent variable is length/height in centimeters. See Table 11 and text for further details.

Table 13a. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \geq 85^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.541	0.508	0.558	0.605	0.496	0.511	0.621	0.434	0.583	0.593	0.507
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.007	0.000	0.010	0.005	0.008	0.006	0.008	0.000	0.009	0.014	0.002
$\alpha \sim f(\alpha)$	0.255	0.284	0.240	0.249	0.259	0.240	0.295	0.237	0.262	0.257	0.254
$\alpha \sim f_i(\alpha)$		0.216	0.284	0.263	0.243	0.248	0.267	0.213	0.271	0.285	0.237
$\alpha \sim f_{-i}(\alpha)$		0.333	0.180	0.234	0.275	0.217	0.308	0.246	0.242	0.240	0.284
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.169	0.135	0.187	0.181	0.161	0.157	0.202	0.112	0.191	0.174	0.166
$W \sim f(W)$	0.101	0.120	0.092	0.090	0.109	0.085	0.142	0.080	0.109	0.106	0.098
$W \sim f_i(W)$		0.050	0.127	0.103	0.094	0.094	0.107	0.068	0.115	0.122	0.087
$W \sim f_{-i}(W)$		0.166	0.042	0.078	0.121	0.064	0.154	0.086	0.093	0.096	0.114
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.332	0.311	0.343	0.340	0.326	0.322	0.358	0.304	0.343	0.338	0.328
$\eta \sim f_i(\eta)$		0.307	0.347	0.344	0.326	0.324	0.354	0.294	0.348	0.357	0.318
$\eta \sim f_{-i}(\eta)$		0.320	0.337	0.340	0.327	0.320	0.361	0.309	0.336	0.328	0.346
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.605	0.532	0.642	0.678	0.554	0.593	0.637	0.558	0.624	0.646	0.578
$X \sim f(X)$	0.596	0.521	0.634	0.659	0.552	0.591	0.611	0.557	0.612	0.630	0.574
$X \sim f_i(X)$		0.560	0.609	0.656	0.557	0.576	0.652	0.525	0.623	0.639	0.568
$X \sim f_{-i}(X)$		0.494	0.670	0.662	0.550	0.630	0.593	0.570	0.585	0.628	0.582
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.581	0.556	0.594	0.635	0.543	0.556	0.649	0.516	0.607	0.611	0.562
$\varepsilon \sim f_i(\varepsilon)$		0.553	0.595	0.630	0.547	0.553	0.653	0.511	0.607	0.616	0.557
$\varepsilon \sim f_{-i}(\varepsilon)$		0.558	0.592	0.640	0.538	0.560	0.647	0.520	0.603	0.608	0.567
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.582	0.509	0.618	0.633	0.546	0.578	0.593	0.546	0.596	0.615	0.561
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.541	0.596	0.626	0.554	0.564	0.634	0.510	0.609	0.625	0.553
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.486	0.652	0.641	0.539	0.618	0.577	0.559	0.566	0.609	0.574

Notes: Benchmark case denotes the observed probability in the sample. Simulations obtained after estimating the dynamic model $y_{it} = \alpha_i + \gamma y_{it-1} + X_{it}\beta + \varepsilon_{it}$, where $\alpha_i = w_i\delta + \eta_i$. $f(\cdot)$ denotes the empirical distribution of the argument. Sample includes data from waves 1-4 of the ECLS-B. See text for the list of covariates and further details.

Table 13b. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 95^{\text{th}} \text{ percentile} \mid y_{it} \geq 95^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.366	0.360	0.369	0.409	0.340	0.354	0.392	0.198	0.420	0.446	0.302
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.118	0.134	0.112	0.113	0.122	0.109	0.140	0.105	0.123	0.122	0.116
$\alpha \sim f_i(\alpha)$		0.088	0.139	0.121	0.112	0.114	0.132	0.084	0.132	0.150	0.101
$\alpha \sim f_{-i}(\alpha)$		0.166	0.070	0.105	0.131	0.098	0.147	0.112	0.102	0.104	0.145
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.031	0.016	0.038	0.044	0.023	0.028	0.038	0.030	0.032	0.043	0.022
$W \sim f(W)$	0.007	0.007	0.007	0.006	0.007	0.006	0.009	0.006	0.007	0.008	0.005
$W \sim f_i(W)$		0.001	0.011	0.007	0.005	0.006	0.007	0.003	0.008	0.012	0.004
$W \sim f_{-i}(W)$		0.011	0.002	0.004	0.010	0.004	0.010	0.005	0.005	0.006	0.008
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.166	0.148	0.174	0.174	0.162	0.162	0.177	0.150	0.172	0.171	0.163
$\eta \sim f_i(\eta)$		0.133	0.183	0.174	0.161	0.160	0.178	0.131	0.179	0.190	0.151
$\eta \sim f_{-i}(\eta)$		0.157	0.164	0.171	0.164	0.162	0.178	0.158	0.156	0.158	0.185
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.419	0.392	0.430	0.465	0.390	0.427	0.400	0.337	0.445	0.462	0.384
$X \sim f(X)$	0.416	0.381	0.431	0.448	0.396	0.427	0.390	0.335	0.442	0.455	0.385
$X \sim f_i(X)$		0.412	0.410	0.445	0.401	0.415	0.437	0.309	0.452	0.462	0.381
$X \sim f_{-i}(X)$		0.354	0.464	0.451	0.392	0.461	0.374	0.347	0.417	0.450	0.393
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.405	0.415	0.401	0.443	0.382	0.390	0.441	0.284	0.444	0.462	0.360
$\varepsilon \sim f_i(\varepsilon)$		0.414	0.403	0.438	0.387	0.386	0.450	0.275	0.447	0.467	0.356
$\varepsilon \sim f_{-i}(\varepsilon)$		0.417	0.398	0.448	0.379	0.393	0.441	0.288	0.440	0.456	0.369
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.413	0.372	0.430	0.443	0.394	0.425	0.385	0.337	0.437	0.450	0.382
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.398	0.413	0.437	0.402	0.412	0.427	0.303	0.450	0.464	0.374
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.356	0.456	0.453	0.385	0.458	0.368	0.352	0.407	0.441	0.397

Notes: See Table 13a and text for further details.

Table 13c. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 50^{\text{th}} \text{ percentile} \mid y_{it} \geq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.831	0.809	0.845	0.852	0.814	0.827	0.842	0.799	0.844	0.852	0.819
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.816	0.978	0.717	0.814	0.818	0.762	0.951	0.772	0.834	0.789	0.832
$\alpha \sim f(\alpha)$	0.621	0.655	0.599	0.618	0.624	0.605	0.661	0.595	0.631	0.623	0.620
$\alpha \sim f_i(\alpha)$		0.606	0.641	0.628	0.615	0.615	0.641	0.594	0.633	0.632	0.617
$\alpha \sim f_{-i}(\alpha)$		0.693	0.545	0.608	0.635	0.581	0.672	0.596	0.633	0.620	0.629
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.848	0.822	0.864	0.867	0.831	0.844	0.857	0.813	0.862	0.852	0.846
$W \sim f(W)$	0.726	0.792	0.685	0.722	0.729	0.699	0.792	0.685	0.742	0.726	0.725
$W \sim f_i(W)$		0.695	0.761	0.740	0.711	0.714	0.759	0.677	0.746	0.736	0.719
$W \sim f_{-i}(W)$		0.858	0.579	0.703	0.748	0.658	0.806	0.689	0.734	0.722	0.734
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.680	0.653	0.697	0.696	0.666	0.673	0.699	0.645	0.695	0.693	0.673
$\eta \sim f_i(\eta)$		0.661	0.690	0.695	0.667	0.674	0.695	0.656	0.690	0.692	0.672
$\eta \sim f_{-i}(\eta)$		0.647	0.706	0.697	0.665	0.669	0.698	0.640	0.707	0.693	0.671
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.851	0.805	0.879	0.875	0.830	0.860	0.828	0.853	0.850	0.854	0.849
$X \sim f(X)$	0.836	0.794	0.862	0.862	0.814	0.844	0.817	0.838	0.836	0.842	0.833
$X \sim f_i(X)$		0.829	0.844	0.860	0.817	0.833	0.848	0.818	0.843	0.846	0.831
$X \sim f_{-i}(X)$		0.768	0.889	0.864	0.812	0.872	0.804	0.846	0.817	0.839	0.837
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.827	0.808	0.838	0.851	0.806	0.822	0.837	0.801	0.837	0.843	0.816
$\varepsilon \sim f_i(\varepsilon)$		0.807	0.839	0.848	0.809	0.822	0.840	0.799	0.837	0.845	0.815
$\varepsilon \sim f_{-i}(\varepsilon)$		0.808	0.838	0.854	0.802	0.826	0.837	0.802	0.836	0.843	0.819
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.810	0.766	0.838	0.835	0.789	0.818	0.791	0.808	0.811	0.818	0.806
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.800	0.819	0.831	0.795	0.806	0.825	0.787	0.820	0.824	0.802
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.742	0.865	0.839	0.784	0.850	0.777	0.818	0.790	0.814	0.811

Notes: See Table 13a and text for further details.

Table 13d. Dynamic Simulations: Weight Z-Scores, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \leq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.431	0.426	0.435	0.443	0.418	0.426	0.443	0.395	0.446	0.468	0.410
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.837	0.982	0.724	0.830	0.846	0.793	0.949	0.798	0.854	0.820	0.847
$\alpha \sim f(\alpha)$	0.617	0.646	0.593	0.614	0.619	0.605	0.645	0.594	0.626	0.627	0.610
$\alpha \sim f_i(\alpha)$		0.594	0.632	0.624	0.610	0.614	0.622	0.592	0.627	0.635	0.606
$\alpha \sim f_{-i}(\alpha)$		0.683	0.537	0.603	0.629	0.579	0.653	0.594	0.626	0.622	0.619
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.613	0.553	0.661	0.633	0.591	0.613	0.615	0.559	0.636	0.648	0.594
$W \sim f(W)$	0.719	0.777	0.674	0.715	0.725	0.698	0.771	0.685	0.734	0.732	0.712
$W \sim f_i(W)$		0.680	0.749	0.734	0.706	0.715	0.737	0.676	0.737	0.740	0.708
$W \sim f_{-i}(W)$		0.847	0.566	0.696	0.743	0.659	0.784	0.688	0.727	0.726	0.721
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.556	0.525	0.581	0.568	0.542	0.556	0.555	0.526	0.568	0.574	0.546
$\eta \sim f_i(\eta)$		0.527	0.577	0.569	0.543	0.559	0.551	0.532	0.567	0.578	0.543
$\eta \sim f_{-i}(\eta)$		0.523	0.585	0.570	0.541	0.552	0.557	0.525	0.575	0.572	0.551
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.435	0.398	0.465	0.462	0.405	0.447	0.407	0.444	0.432	0.432	0.437
$X \sim f(X)$	0.440	0.401	0.470	0.464	0.412	0.451	0.413	0.442	0.439	0.442	0.439
$X \sim f_i(X)$		0.436	0.448	0.460	0.416	0.436	0.452	0.413	0.450	0.451	0.434
$X \sim f_{-i}(X)$		0.377	0.503	0.467	0.410	0.488	0.397	0.455	0.411	0.436	0.447
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.431	0.428	0.434	0.453	0.407	0.429	0.436	0.402	0.444	0.450	0.421
$\varepsilon \sim f_i(\varepsilon)$		0.425	0.437	0.449	0.411	0.428	0.440	0.396	0.446	0.458	0.417
$\varepsilon \sim f_{-i}(\varepsilon)$		0.431	0.430	0.457	0.403	0.435	0.434	0.405	0.438	0.447	0.429
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.441	0.405	0.469	0.464	0.415	0.451	0.417	0.442	0.441	0.445	0.439
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.431	0.451	0.457	0.423	0.436	0.455	0.408	0.454	0.460	0.429
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.387	0.496	0.472	0.407	0.488	0.401	0.456	0.410	0.437	0.454

Notes: See Table 13a and text for further details.

Table 14a. Dynamic Simulations: Height, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \geq 85^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.600	0.576	0.615	0.626	0.580	0.611	0.574	0.585	0.606	0.605	0.598
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.190	0.225	0.169	0.062	0.292	0.175	0.228	0.135	0.213	0.198	0.186
$\alpha \sim f(\alpha)$	0.380	0.400	0.368	0.332	0.418	0.373	0.397	0.355	0.390	0.387	0.376
$\alpha \sim f_i(\alpha)$		0.351	0.403	0.368	0.381	0.385	0.368	0.377	0.381	0.383	0.379
$\alpha \sim f_{-i}(\alpha)$		0.435	0.318	0.295	0.456	0.342	0.410	0.345	0.416	0.392	0.369
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.396	0.367	0.413	0.386	0.403	0.401	0.383	0.386	0.400	0.373	0.409
$W \sim f(W)$	0.292	0.323	0.274	0.210	0.357	0.281	0.320	0.252	0.308	0.306	0.284
$W \sim f_i(W)$		0.256	0.316	0.258	0.300	0.301	0.266	0.275	0.297	0.284	0.296
$W \sim f_{-i}(W)$		0.370	0.215	0.163	0.414	0.232	0.340	0.242	0.335	0.319	0.264
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.444	0.430	0.452	0.438	0.448	0.447	0.435	0.437	0.446	0.438	0.447
$\eta \sim f_i(\eta)$		0.430	0.451	0.439	0.447	0.447	0.436	0.449	0.441	0.447	0.442
$\eta \sim f_{-i}(\eta)$		0.431	0.450	0.437	0.449	0.445	0.436	0.433	0.457	0.433	0.456
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.607	0.565	0.632	0.622	0.594	0.623	0.568	0.630	0.597	0.591	0.616
$X \sim f(X)$	0.597	0.564	0.616	0.607	0.588	0.612	0.559	0.622	0.586	0.589	0.601
$X \sim f_i(X)$		0.581	0.605	0.605	0.591	0.606	0.575	0.595	0.598	0.597	0.596
$X \sim f_{-i}(X)$		0.554	0.633	0.608	0.587	0.630	0.551	0.634	0.556	0.584	0.610
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.597	0.572	0.612	0.619	0.580	0.605	0.577	0.586	0.601	0.598	0.596
$\varepsilon \sim f_i(\varepsilon)$		0.572	0.612	0.611	0.588	0.606	0.576	0.589	0.600	0.599	0.597
$\varepsilon \sim f_{-i}(\varepsilon)$		0.574	0.611	0.628	0.571	0.603	0.580	0.585	0.605	0.597	0.597
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.589	0.559	0.607	0.599	0.581	0.603	0.553	0.614	0.578	0.581	0.593
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.573	0.596	0.591	0.590	0.597	0.569	0.590	0.590	0.589	0.588
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.548	0.622	0.606	0.573	0.620	0.546	0.625	0.554	0.575	0.602

Notes: Benchmark case denotes the observed probability in the sample. Simulations obtained after estimating the dynamic model $y_{it} = \alpha_i + \gamma y_{it-1} + X_{it}\beta + \varepsilon_{it}$, where $\alpha_i = w_i\delta + \eta_i$. $f(\cdot)$ denotes the empirical distribution of the argument. Sample includes data from waves 1-4 of the ECLS-B. See text for the list of covariates and further details.

Table 14b. Dynamic Simulations: Height, $\Pr(y_{it} \geq 95^{\text{th}} \text{ percentile} \mid y_{it} \geq 95^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.365	0.344	0.377	0.372	0.360	0.355	0.387	0.353	0.370	0.319	0.393
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\alpha \sim f(\alpha)$	0.092	0.102	0.087	0.061	0.112	0.088	0.100	0.080	0.096	0.095	0.090
$\alpha \sim f_i(\alpha)$		0.080	0.100	0.074	0.094	0.094	0.082	0.085	0.093	0.090	0.091
$\alpha \sim f_{-i}(\alpha)$		0.116	0.069	0.050	0.128	0.072	0.105	0.077	0.101	0.095	0.086
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.020	0.008	0.027	0.020	0.020	0.021	0.017	0.015	0.022	0.022	0.019
$W \sim f(W)$	0.007	0.007	0.007	0.002	0.010	0.006	0.008	0.004	0.008	0.007	0.007
$W \sim f_i(W)$		0.004	0.008	0.003	0.005	0.007	0.006	0.005	0.007	0.007	0.006
$W \sim f_{-i}(W)$		0.009	0.004	0.001	0.015	0.005	0.008	0.004	0.009	0.008	0.006
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.136	0.131	0.139	0.125	0.144	0.134	0.141	0.129	0.139	0.133	0.138
$\eta \sim f_i(\eta)$		0.125	0.141	0.127	0.138	0.132	0.139	0.125	0.137	0.137	0.133
$\eta \sim f_{-i}(\eta)$		0.134	0.131	0.120	0.146	0.129	0.142	0.129	0.137	0.128	0.142
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.350	0.320	0.366	0.346	0.354	0.369	0.309	0.426	0.322	0.297	0.382
$X \sim f(X)$	0.353	0.332	0.365	0.360	0.349	0.368	0.322	0.416	0.330	0.298	0.386
$X \sim f_i(X)$		0.346	0.356	0.358	0.353	0.362	0.337	0.388	0.341	0.305	0.383
$X \sim f_{-i}(X)$		0.322	0.380	0.362	0.348	0.384	0.315	0.429	0.304	0.297	0.395
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.304	0.306	0.303	0.311	0.300	0.301	0.311	0.308	0.303	0.264	0.328
$\varepsilon \sim f_i(\varepsilon)$		0.303	0.304	0.302	0.307	0.302	0.310	0.308	0.302	0.267	0.326
$\varepsilon \sim f_{-i}(\varepsilon)$		0.307	0.301	0.319	0.292	0.298	0.310	0.306	0.304	0.263	0.330
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.357	0.336	0.368	0.364	0.353	0.372	0.325	0.415	0.335	0.306	0.388
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.349	0.361	0.358	0.360	0.365	0.339	0.392	0.345	0.315	0.382
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.328	0.381	0.373	0.346	0.385	0.320	0.425	0.313	0.301	0.398

Notes: See Table 14a and text for further details.

Table 14c. Dynamic Simulations: Height, $\Pr(y_{it} \geq 50^{\text{th}} \text{ percentile} \mid y_{it} \geq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.785	0.790	0.782	0.785	0.786	0.789	0.777	0.793	0.782	0.780	0.788
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.897	0.948	0.865	0.833	0.954	0.878	0.945	0.849	0.916	0.907	0.891
$\alpha \sim f(\alpha)$	0.669	0.693	0.655	0.615	0.717	0.662	0.688	0.646	0.679	0.678	0.665
$\alpha \sim f_i(\alpha)$		0.658	0.681	0.649	0.689	0.672	0.660	0.678	0.666	0.667	0.670
$\alpha \sim f_{-i}(\alpha)$		0.717	0.617	0.581	0.745	0.632	0.698	0.632	0.710	0.684	0.654
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.865	0.860	0.868	0.857	0.872	0.871	0.851	0.855	0.869	0.859	0.869
$W \sim f(W)$	0.779	0.816	0.756	0.704	0.845	0.767	0.809	0.742	0.794	0.792	0.772
$W \sim f_i(W)$		0.758	0.801	0.753	0.813	0.787	0.763	0.772	0.783	0.765	0.788
$W \sim f_{-i}(W)$		0.857	0.691	0.655	0.877	0.719	0.827	0.731	0.819	0.807	0.745
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.715	0.707	0.720	0.699	0.729	0.719	0.704	0.710	0.717	0.710	0.718
$\eta \sim f_i(\eta)$		0.713	0.717	0.698	0.731	0.719	0.706	0.725	0.711	0.716	0.715
$\eta \sim f_{-i}(\eta)$		0.704	0.724	0.702	0.727	0.721	0.703	0.704	0.732	0.705	0.726
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.787	0.771	0.797	0.797	0.778	0.800	0.754	0.806	0.779	0.781	0.790
$X \sim f(X)$	0.762	0.748	0.771	0.766	0.759	0.772	0.737	0.779	0.755	0.759	0.764
$X \sim f_i(X)$		0.762	0.761	0.765	0.760	0.767	0.750	0.756	0.764	0.765	0.760
$X \sim f_{-i}(X)$		0.738	0.784	0.768	0.757	0.787	0.730	0.790	0.731	0.754	0.771
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.804	0.803	0.805	0.806	0.803	0.809	0.792	0.807	0.803	0.806	0.804
$\varepsilon \sim f_i(\varepsilon)$		0.805	0.805	0.799	0.810	0.810	0.792	0.811	0.802	0.806	0.804
$\varepsilon \sim f_{-i}(\varepsilon)$		0.803	0.806	0.812	0.798	0.808	0.793	0.806	0.807	0.807	0.803
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.749	0.735	0.758	0.752	0.746	0.759	0.723	0.766	0.742	0.745	0.751
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.750	0.748	0.745	0.753	0.753	0.737	0.747	0.750	0.752	0.747
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.724	0.772	0.758	0.740	0.773	0.717	0.773	0.722	0.741	0.758

Notes: See Table 14a and text for further details.

Table 14d. Dynamic Simulations: Height, $\Pr(y_{it} \geq 85^{\text{th}} \text{ percentile} \mid y_{it} \leq 50^{\text{th}} \text{ percentile})$.

	Full	Race		Gender		Urban Status		Education		SES	
	Sample	White	Non-White	Male	Female	Urban	Non-Urban	Non-College	College	Low SES	High SES
Benchmark	0.179	0.176	0.181	0.168	0.193	0.185	0.165	0.200	0.170	0.196	0.169
Panel I. Own Xs, $\varepsilon=0$, and											
$\alpha=E[\alpha]$	0.183	0.206	0.163	0.071	0.319	0.160	0.239	0.117	0.210	0.218	0.162
$\alpha \sim f(\alpha)$	0.383	0.401	0.368	0.345	0.428	0.373	0.407	0.357	0.393	0.393	0.377
$\alpha \sim f_i(\alpha)$		0.350	0.401	0.381	0.389	0.385	0.378	0.380	0.383	0.387	0.380
$\alpha \sim f_{-i}(\alpha)$		0.436	0.319	0.310	0.466	0.342	0.419	0.348	0.418	0.396	0.370
Panel II. Own Xs, $\eta=0$, $\varepsilon=0$, and											
$W=W_i$	0.148	0.111	0.178	0.139	0.157	0.156	0.127	0.125	0.157	0.145	0.149
$W \sim f(W)$	0.296	0.321	0.274	0.231	0.375	0.280	0.334	0.255	0.313	0.314	0.285
$W \sim f_i(W)$		0.254	0.315	0.280	0.316	0.300	0.278	0.278	0.302	0.291	0.296
$W \sim f_{-i}(W)$		0.369	0.215	0.180	0.431	0.231	0.357	0.245	0.340	0.326	0.264
Panel III. Own Xs, own Ws, $\varepsilon=0$, and											
$\eta \sim f(\eta)$	0.297	0.276	0.314	0.292	0.303	0.301	0.288	0.283	0.303	0.293	0.299
$\eta \sim f_i(\eta)$		0.273	0.318	0.295	0.302	0.303	0.287	0.288	0.301	0.302	0.295
$\eta \sim f_{-i}(\eta)$		0.281	0.310	0.288	0.307	0.300	0.288	0.282	0.308	0.288	0.309
Panel IV. Own α , $\varepsilon=0$, and											
$X=E[X]$	0.176	0.158	0.191	0.179	0.172	0.189	0.144	0.200	0.166	0.168	0.181
$X \sim f(X)$	0.204	0.186	0.219	0.207	0.201	0.208	0.193	0.230	0.193	0.202	0.205
$X \sim f_i(X)$		0.194	0.212	0.205	0.203	0.204	0.205	0.208	0.201	0.207	0.201
$X \sim f_{-i}(X)$		0.179	0.229	0.207	0.200	0.219	0.187	0.239	0.174	0.199	0.210
Panel V. Own Xs, own α , and											
$\varepsilon \sim f(\varepsilon)$	0.158	0.148	0.166	0.159	0.156	0.160	0.154	0.162	0.156	0.170	0.150
$\varepsilon \sim f_i(\varepsilon)$		0.146	0.167	0.154	0.161	0.160	0.150	0.163	0.156	0.173	0.149
$\varepsilon \sim f_{-i}(\varepsilon)$		0.150	0.163	0.164	0.151	0.158	0.154	0.163	0.155	0.168	0.153
Panel VI. Own α and											
$X, \varepsilon \sim f(X, \varepsilon)$	0.214	0.197	0.229	0.217	0.212	0.218	0.204	0.241	0.203	0.213	0.215
$X, \varepsilon \sim f_i(X, \varepsilon)$		0.204	0.224	0.210	0.219	0.215	0.214	0.220	0.211	0.220	0.211
$X, \varepsilon \sim f_{-i}(X, \varepsilon)$		0.193	0.237	0.223	0.205	0.228	0.201	0.249	0.186	0.210	0.223

Notes: See Table 14a and text for further details.